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The trap of climate change-induced "natural" disasters and inequality

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ABSTRACT

The purpose of the present paper is to disentangle the mechanisms that connect climate change-induced disasters, inequality and vulnerability by accounting for both directions of causality. We do so by means of a simultaneous equations approach on a panel of 149 countries from 1992 to 2018. The empirical analysis reveals that countries with higher levels of income inequality suffer greater damages when hit by a natural disaster. At the same time, inequality is found to increase the number of people affected by disasters. Our analysis discloses the existence of a vicious cycle that keeps some countries stuck in a disasters-inequality trap.

1. Introduction

Natural disasters have devastating impacts on societies and impose exorbitant tolls in terms of casualties, material deprivation and altered power relations. Since the 1970 s the frequency of natural disasters worldwide has increased dramatically (Yamamura, 2015) and so have the economic damages to them ascribed, in spite of improvements in early warning systems and post-disaster recovery measures (Coronese et al., 2019). According to the Intergovernmental Panel on Climate Change (IPCC), these events will become even more recurrent and intense due to growing concentration of greenhouse gases in the atmosphere (IPCC, 2018). Most studies focus on single catastrophic events and assess whether the associated damages widen inequality or, vice versa, whether more egalitarian societies mitigate the severity of the aftermath. Groeschl and Noy (2020) recently called for more systematic research into the linkages between climate change, frequency of natural disasters and socioeconomic vulnerability. The joint assessment of both the impact of natural disasters on inequality and of the role of inequality on the relative vulnerability to damages due to disasters can shed light into the trend of growing damages first reported by Coronese et al. (2019).

The purpose of the present paper is to disentangle the mechanisms that connect vulnerability to climate change-induced disasters and to inequality by accounting for both directions of causality. We do so by means of a simultaneous equations approach on a panel of 149 countries from 1992 to 2018. The main finding is that higher levels of income inequality, measured by the Gini index, are associated with a greater number of people affected by natural disasters. At the same time, the higher the human toll the wider is the inequality gap. Further, the panel analysis brings to the fore the dynamic character of these phenomena, whereby the cumulative impacts of repeated disasters on some locations trigger a vicious cycle, that we label disaster-inequality trap.

The remainder of the paper is organised as follows. Section 2 reviews key literature on the causal relations between natural disasters and income inequality. Section 3 outlines the modelling framework, the panel database and relevant econometric details. Section 4 discusses main results and Section 5 concludes with key relevant policy implications for future adaptation strategy design.

2. Natural disasters and income inequality

2.1. Background

The literature on the distribution of adverse impacts of natural disasters on different economic and social groups is increasingly focussed on the pathways that connect vulnerability to environmental shocks. Ample empirical evidence shows that climate disasters are a bigger burden for countries that cannot afford preventive measures, or in which access to resources that ensure resilience is limited to a small share of the population (Berlemann and Wenzel, 2018; Noy, 2009; Tol and Leek, 1999). A similar cross-country gap exists in long-term changes of climate and weather conditions that affect countries' development paths

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depending on geography. To. illustrate, countries in high latitudes have been found to benefit from global warming at the expense of countries in lower latitudes (Diffenbaugh and Burke, 2019).

Kellenberg and Mobarak (2008) show that the relationship between economic development and disaster risk associated to flooding, landslides and windstorms has an inverted U shape. This implies that at early stages of development the risk of damage is high because investments in preventive measures may not suffice to preserve productive assets. As countries move to later stages of development, the risk of damage is lower due to greater affordability of precautionary measures. Such a heuristic holds over different, and more comprehensive, definitions of economic development that include educational attainment, openness to trade or the maturity of the financial sector (Toya and Skidmore, 2007).

Another issue of interest is that the impact of natural disasters is uneven across segments of the population within a country (Benson et al., 2001; Deuchert and Felfe, 2015; Heijmans, 2001; Sakai et al., 2017). Empirical studies on this usually fall in one of two categories.

One strand of research consists of case studies based on quasi-experimental methods to compare growth and inequality before and after specific events. Natural disasters are classic exogenous shocks that are amenable to natural experiments and counterfactual type of analysis. There is plenty of literature on the short and long-term socioeconomic impacts, including inequality, of specific extreme events (Baez and Santos, 2007; Belasen and Polachek, 2009; Mottaleb et al., 2013; Sakai et al., 2017; Thiede, 2014). To illustrate, Lynham et al (2017) find that after the tsunami that hit Hawaii in 1960, wages remained constant but unemployment increased, family businesses failed and a large portion of the population was displaced. A counterfactual study by Bui et al (2014) finds that a series of natural disasters occurred in Vietnam over a period of 60 months led to negative outcomes on both income and expenditure levels and contributed to exacerbate poverty and inequality. Carter et al (2007) focus on long-term asset recovery in the aftermaths of the 1998 Hurricane Mitch in Honduras and of a prolonged drought that affected Ethiopia from 1998 to 2000. The authors report a critical threshold in asset ownership below which recovery is not feasible and poor households are irreversibly stuck in a poverty trap. Similar results emerge from studies on other regions of the world, such as Mexico (Rodriguez-Oreggia et al., 2013), rural India (Sedova et al., 2020) and Nepal (Pradhan et al., 2007).

Further, in societies with wide income gaps lack of access to resources pushes households at the bottom of distribution not to seek insurance coverage but to rely on other means to cope with momentary income shock, such as employment of child labour, sale of productive goods (Sawada and Takasaki, 2017), changes in both agricultural practices and diet, out-migration of different length periods (De Waal, 2005). These solutions however often push households even deeper into the poverty trap (Banerjee and Duflo, 2011; Lybbert and Barrett, 2011). Conversely, traditional adaptation measures such as diversification of income (Adger, 2006; Eriksen et al., 2005), drought-resistant crops or alternative storage strategies (Eakin and Conley, 2002; Thomas et al., 2007) prove to be effective against punctual events, but less so in case of repeated shocks (Kallis, 2008). Last but not least, strain in the aftermath of a disaster is often fertile ground for collateral effects such as the breakout of armed conflicts (Ide et al., 2020), unrest among the civilian population in the struggle to access humanitarian aids (Hendrix and Salehyan, 2012) as well as mass outmigration (Abel et al., 2019).

A second relevant strand of literature includes longitudinal studies on the effect of multiple disasters on poverty, growth and inequality. The evidence is decidedly mixed. For instance, Hallegatte and Ghil (2008) report the counterintuitive result that economies in recession suffer less the impact of natural disasters, which can instead act as a positive stimulus. This is the case of countries in which resources are not fully utilized and extreme events trigger the mobilization of idle capacity. There is also evidence of GDP increases relative to pre-event level (Albala-Bertrand, 1993) due to a “productivity effect” or “Schumpeterian creative destruction effect”, whereby damage to buildings and to infrastructure offers an opportunity for reconstruction (Benson and Clay, 2004; Okuyama, 2003; Stewart and Fitzgerald, 2001). However, not all countries have the necessary financial and technological means to transform post-disaster strain into an opportunity and, more cogently, GDP growth does not necessarily imply widely shared prosperity. As a matter of fact, the evidence indicates that structural shocks typically benefit primarily the dominant classes (Klein, 2007; Lowenstein, 2015). Furthermore, the time needed for reconstruction and the efficiency of reconstruction may be subjected to financial or technical constraints that can widen the gap between the affected and the not affected (Hallegatte and Przyluski, 2010).

While most studies focus on the economic consequences of natural disasters, be they single case studies or cross-country studies, very few investigate whether and how income inequality exacerbates the impacts of catastrophic events. Until recently, a country’s level of inequality was considered the outcome of economic performance but was rarely contemplated as a determinant (Anbarci et al., 2005). Likewise, research on the impact of natural disasters had seldom considered inequality as a factor for vulnerability. This prevailing view changed when scholars sought to contrast the established notion of natural disasters as phenomena merely dependent on geographical location, on event-specific features, such as magnitude, intensity and frequency (Cutter, 2006), but completely detached from human activities (Fordham et al., 2013). New research pointed to a host of crucial factors that are not casual but, rather, are moulded by local power relations and socio-economic inequality (Bankoff, 2006; Ryder, 2017). Among these forces are access to resources such as private capital, disaster warning systems, emergency response, insurance, information and communication networks (Cinner et al., 2018) as well as resilience and adaptive capacity to extreme events. Under this perspective, extreme events are understood as human-related rather than merely natural phenomena (Gaillard et al., 2014; O’Keefe et al., 1976) in that they qualify as ‘disasters’ only when they cause loss of lives or damages that undermine equal access to the resources that can prevent or mitigate the impacts (Thomas et al., 2018).

The seminal study on the economic and political factors that determine countries’ vulnerability to catastrophic events by Kahn (2005) finds that the death toll is lower in richer countries, after controlling for population and number of disasters per year, due to availability of prevention measures and of stricter law enforcement. Furthermore, higher income inequality is associated with higher death tolls from natural catastrophes. Conversely, the death toll is lower, ceteris paribus, in countries with stronger (democratic) institutions. Anbarci et al. (2005) further confirm this in a study on the aftermath of 269 earthquakes between 1960 and 2002 all over the world. In particular, they conclude that while the occurrence of a catastrophic event is a purely natural phenomenon, the resulting death toll is ascribable to economic, political and institutional factors. Inequality therefore emerges from this literature as a barrier to society’s ability to achieve an agreeable distribution of the collective effort to limit vulnerability.

Lack of access to mitigation and prevention measures is to natural disasters what ‘entitlement relations’ are to famines (Sen, 1981). Uneven distribution of income (vertical inequality), of power and of political representation across social groups (horizontal inequality) leads to unequal access to prevention and recovery measures, and to financial resources (Vásquez-León et al., 2003; Watts and Bohle, 1993). In this vein, several studies show that marginalized ethnic groups experience higher mortality and asset loss (Liang et al., 2001; Klinenberg, 2002; Amarasiri de Silva, 2009; Dash, 2013). Gender inequality also affects the uneven distribution of disasters’ incidence since women suffer from reduced mobility to the non-agricultural sector as well as to limited access to warning information (Chowdhury et al., 2021, Paudel and Ryu, 2018), which increases post-disaster vulnerability to damages (Cutter, 2017). Likewise, health-related risks due to extreme geophysical events (Gouveia et al., 2003) as well as waterborne diseases emerging as indirect effects of floods (Cutter et al., 2000; Bartlett, 2008; Khan et al., 2011), are stratified across age groups.

2.2. Gaps and research hypotheses

The prevailing orientation in the literature is to consider disasters as exceptional and independent events from one another. This is an ideal setting for counterfactual pre- vs post-comparison but falls short of explaining the growing frequency (Rosenzweig et al., 2008) and the increasing magnitude of the associated damages (Coronese et al., 2019). In this vein, we follow Groeschl and Noy's (2020) suggestion to frame the analysis of natural disasters in a climate change perspective by widening the array of disasters as well as the locations and time horizon. Further, we propose that a self-reinforcing dynamic may be at play whereby income inequality amplifies the magnitude of cumulative damages in locations that have suffered repeated catastrophic events.

Our conjecture is that inequality hinders reconstruction and recovery thus further reducing access to basic services to the poorest segments of the population. Accordingly, we test the simultaneous validity of the two causal relations discussed in the literature: first, that natural disasters affect inequality and, second, that income distribution affects resilience to the damages caused by natural disasters. Such an exercise is articulated in three hypotheses.

Natural disasters cause various forms of damage such as casualties, health impairment, destruction of physical assets and loss of economic activities. The magnitude of damages is the first criterion for classifying a natural event as disaster, but the vulnerability of the location that is hit also plays a role (Gaillard, 2010). More unequal societies bear the brunt of natural disasters in terms of death toll and affected individuals because marginalised portions of the population are in locations with higher exposure to natural hazards (Heijmans, 2001; Yamamura, 2015). In these contexts, public insurance fails to provide precautionary coverage while private insurance is simply unaffordable. In the background stands the lack of solid institutions that, combined with ineffective use of public resources, prevent the implementation of climate change adaptation and mitigation policies that could minimise the impact of disasters and protect disadvantaged groups (Borgerhoff Mulder et al., 2009). Accordingly, our first hypothesis is:

Hypothesis 1. *Unequal societies suffer greater physical damages due to natural disasters.*

One of the consequences of unequal income distribution is that wealthier households can afford better prevention and recovery measures that reduce the prospective burden of extreme events and, also, facilitate the process of reconstruction. On the other hand, in the absence of institutions that facilitate generally more equitable access to public services (Acemoglu and Robinson, 2009), and to prevention and recovery systems in particular, extreme events can widen inequality as low-income households suffer severe consequences in terms of health and/or material losses. Further, in the case of frequent repeated events, unequal societies may find themselves trapped in a permanent state of reconstruction that diverts financial resources towards urgent recovery activities, and leaves little to no margin for planning and implementing proper prevention measures (Hallegatte and Przyluski, 2010). Thereby the extent to which climate-related phenomena cause disasters (IPCC, 2012) depends also on whether differential vulnerability amplifies or not the effect of an event. Additionally, although the media tend to report only major disasters, the cumulative effect of small disasters in communities that are repeatedly hit can cause more damages than a single major catastrophe (Alexander, 1993; Alexander, 2000; Birkmann, 2006; Marulanda et al., 2008; Marulanda et al., 2010; Marulanda et al., 2011; UNISDR, 2009). Building on this, we formulate the second hypothesis:

Hypothesis 2. *Natural disasters increase income inequality*.

We posit that when a given society suffers repeated disasters, the cumulative socio-economic impacts of multiple extreme events amplifies the scenario depicted in the first two hypotheses. Thereby the two hypotheses are interconnected and reinforce one another in that mutual causality between the number of people affected by extreme events and income inequality explains the destructive ripple effect observed in several developing countries regardless of the adaptation plans in place. In these contexts, marginalized groups and more vulnerable households bear most of the damage. As per the second hypothesis, this widens the gap and the polarization in income distribution because the cumulation of extreme events and of the associated losses push households in hard-hit societies in the lower tails of income distribution. Accordingly, we formulate the third hypothesis:

Hypothesis 3. *Unequal societies suffer from a vulnerability-disaster trap whereby damages due to natural disasters further widen income inequality and further reduce resilience.*

3. The database

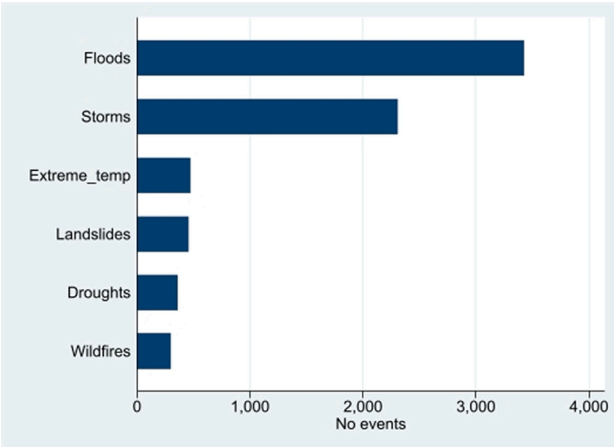
3.1. Dependent variables

Our analysis is based on a panel database of 149 countries over the period 1992–2018. To test Hypothesis 1, the dependent variable *HIT* represents the impacts of disasters as the sum of death toll and people affected by each event. These variables are built using the Emergency Events Database (EM-DAT), developed by the Centre for Research on the Epidemiology of Disasters (CRED), the most comprehensive source on natural catastrophes (Wirtz et al., 2014). This database integrates information from different sources to provide data on 22,000 mass disasters all over the world since 1900. To be classified as a disaster and be included in EM-DAT, an event must meet at least one of the following criteria: i) 10 or more casualties; ii) 100 or more people affected or injured or homeless; iii) the country declared a state of emergency and/or an appeal for international assistance.

We focus on a subset of climate-related natural disasters, namely: floods, landslides and storms ("wet disasters") and droughts, extreme temperatures and wildfires ("dry disasters"). For each disaster, we gather information on the number of events per country/ year from 1992 to 2018, on the associated death toll and on the number of affected people (the sum of all physically injured individuals, people requiring immediate assistance during an emergency situation including those who are homeless as a direct consequence of the event). We compute the dependent variable *HIT* as the sum of the death toll and the number of people affected by each disaster, which is the dependent variable in the disaster equation and one of the covariates in the inequality equation. To allow for direct comparability of the entity of disasters across countries independently from population density, we standardize the dependent variable by previous year's population (Klomp and Valckx, 2014).

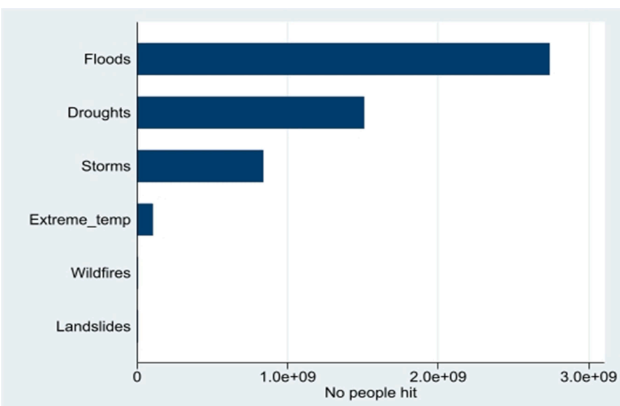
Different disasters occur with variable frequency and have different impacts (Figs. 1-2). While floods were the most recurrent and most devastating events between 1992 and 2018, droughts, despite low frequency, rank second in terms of number of people hit. In the same way, Figs. 3-4 show that some continents exhibit higher exposure to some typologies of (and impacts from) natural disasters. While Latin America and the Caribbean are the regions mostly hit by (especially wet) disasters, Asia and Africa are the regions mostly affected by dry disasters.

As for Hypothesis 2, the measure of inequality is the Gini index (hereafter *Gini*). This is the most widely accepted measure of income distribution also by virtue of the wide data availability. We collect data on the Gini index, computed on disposable income (post-tax, post-transfer), from the Standardized World Income Inequality Database (SWIID) developed by Solt (2019), which offers, to the best of our knowledge, the widest coverage of income inequality across countries and over time.



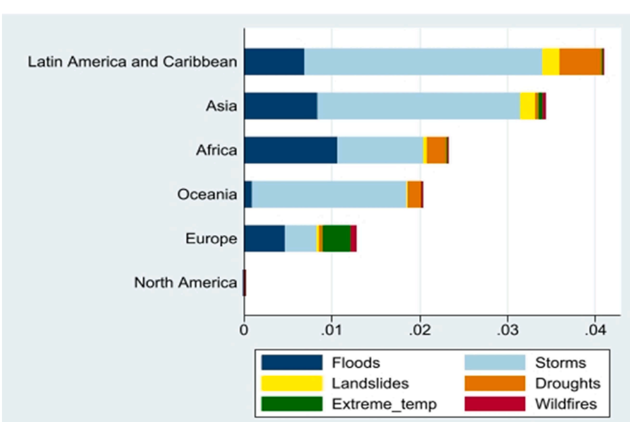
Source: authors' elaboration on EM-DAT

Fig. 1. Number of natural disasters by typology 1992–2018 *Source: authors' elaboration on EM-DAT.*



Source: authors' elaboration on EM-DAT

Fig. 2. Number of persons hit by disaster typology 1992–2018 *Source: authors' elaboration on EM-DAT.*

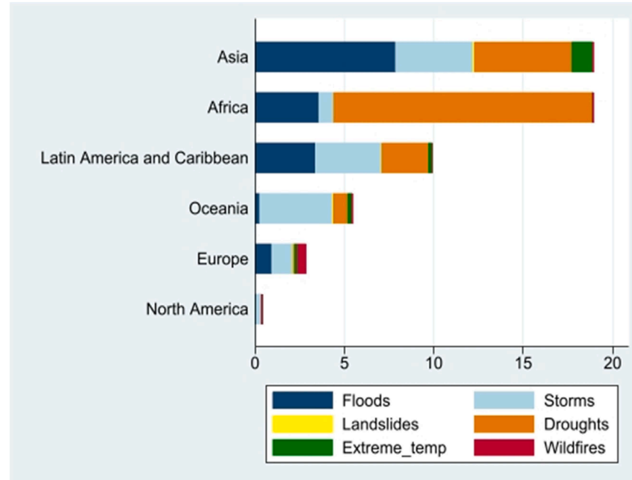


Source: authors' elaboration on EM-DAT and WDI

Fig. 3. Number of natural disasters by continent 1992–2018 (normalized by land area) *Source: authors' elaboration on EM-DAT and WDI.*

3.2. Explanatory variables

The main explanatory variables have been identified following prior empirical studies and can be classified in four groups. The first three concern the analysis of disaster magnitude and include socioeconomic variables; frequency of climate-related disasters and other climate-sensitive geographical features; and other country-based controls. The last set of explanatory variables concern the regression on inequality and include proxies of social norms. Selected variables from the first group related to socioeconomic conditions are also valid regressors for the inequality equation. Accordingly, in the fourth group we include only those regressors that are strictly related to inequality, and not used in the disaster equation.



Source: authors' elaboration on EM-DAT and WDI

Fig. 4. People hit by continent 1992–2018 (normalized by previous year's population) *Source: authors' elaboration on EM-DAT and WDI.*

Socioeconomic variables have been selected to represent what Fankhauser and McDermott (2014) define the "adaptation deficit", which we disentangle in demand and supply effects. As regards the former, wealthier societies exhibit higher willingness to pay for "climate security" that increases with disposable income. As regards the supply side, adaptation is enhanced by factors such as quality of services or capital investments financed by public budget. Accordingly, we include information on the gross domestic product (GDP) per capita (expressed in constant US$ international purchasing power parity 2011) as a proxy of the willing to pay for a safer environment. To complement purely income-based information, following Russo et al. (2019) we also collect data for the Human Development Index (HDI) related to the two components of life expectancy and education attainments according to the United Nations Development Program (UNDP) methodology, representing an additional measure of demand for resilience net of GDP per capita (hereafter referred as NHDI).

Along with recent analyses by Chowdhury et al. (2021) and Paudel and Ryu (2018), we control for gender disparity as an additional element of vulnerability to disasters for societies in which women face larger constraints in accessing resources. Relying on the original methodology of the UNDP (2020), we consider the inequality in education attainment (as the ratio between the female and male literacy rate) and in participation to the labour market (as the ratio between the female and male employment rate). The gender inequality index results from the average between the two components (GDI) and is used to compute a gender-qualified human development index (GNHDI) as the average between the NHDI and GDI. The GDI is not normalised, so that GDI < 1 applies when society is unbalanced in favour of males while for GDI > 1 of women. The gender-qualified indices are computed as the average between the full index (HDI) or the net index (NHDI) and the GDI. Accordingly, given that GDI may assume values higher than 1, also the gender-corrected indices, GHDI and GNHDI, may assume values higher than 1.

As regards the supply side of adaptation deficit, we capture governments' propensity to increase the resilience to environmental damages with two indicators: i) government final consumption expenditure (as % of GDP) as a proxy of ordinary management efforts; ii) net investment in nonfinancial assets (as % of GDP) as a proxy of the attitude of the public sector to maintain and expand physical infrastructures.

To account for disasters' patterns and geographical location, we include two controls specifically related to the frequency of disasters. The first is the sum of all events in each country/year both taken all together and, in line with the distinction applied to the dependent variable, disentangled into wet and dry typologies. The second is the cumulative effect of the repeated exposure to extreme events in previous years. As discussed above, this is a key aspect of our framework whereby economic and physical damages due to catastrophic events also depend on prior damages suffered by the same country in the aftermath of similar events. The panel structure of the data allows us to control for the frequency of current events and for the cumulative number of past disasters. The latter is the sum of all past events in a country up to the time of estimation, and accounts for the potential trap of a permanent state of reconstruction. The rationale is that as governments are forced to devote financial resources to natural disaster recovery efforts in prevention measures are reduced in a typical public budget trade-off context. These countries are therefore more likely to experience higher damages and, simultaneously, higher income inequality. As a final control, we introduce continent dummies excluding Europe taken as the benchmark to limit multi-collinearity.

To capture the geographical dimension of climate, we include two dummy variables related to the presence of Oceanic Niño Index (ONI) (Source: National Oceanic and Atmospheric Administration, NOAA). The ONI is based on variations of sea surface temperatures from the average to predict the phenomenon of El Niño – Southern Oscillation (ENSO), which triggers extreme climatic events. This phenomenon has two components: El Niño and La Niña conditions. The former occurs when the equatorial Pacific has warmer than normal surface water and weaker than normal east winds. As a result, instead of falling over Indonesia, tropical rains shift eastward, winters in the north-western regions of North America are warmer than average, while precipitations in south-eastern regions are more abundant than average (NOAA, 2009). On the contrary, the occurrence of La Niña coincides with cooler surface waters and stronger than normal east winds that shift tropical rains westward relative to Indonesia making Atlantic hurricanes more likely and North American winter cooler than average (NOAA, 2009). The ONI is computed as a three-month average in sea surface temperature relative to a 30-year average in the same three months of the calendar year. When ONI is greater than or equal to $+0.5$ °C, an El Niño condition prevails in a specific three-month season; when ONI is less than or equal to -0.5 °C a La Niña condition prevails in the same period. If values of sea surface temperature in a three-month season are comprised between $+0.5$ °C and -0.5 °C, that season is said to be neutral. Subsequently, the values of the three-month seasons are aggregated over each calendar year to establish the prevalence of El Niño, La Niña or neutral condition.

The third group of country-based control variables in the disaster equation includes two factors to account for damage magnitude. The first is the surface area covered by administrative boundaries of each country (in km^2). Ceteris paribus, we expect that larger territorial extension leads to higher dispersion of the damages across the population, and therefore, greater resilience. The second factor is the share of population based in rural areas, which is considered to be more exposed to natural hazards, especially in developing countries (Chapagain and Raizada, 2017).

The fourth group of covariates captures social norms that influence income inequality and that are also expected to indirectly influence vulnerability to disasters. First, countries with well-functioning and democratic institutions generally exhibit lower income distribution inequality (Chong and Calderón, 2000). Second, in line with the definition of "adaptation deficit", institutional quality might ensure a better resilience and adaptation capacity to disasters. The variable is based on the simple average of the six indices in the Worldwide Governance Indicators (WGI) database (Source: World Bank). Further, ethnic marginalisation is considered a major source of inequality in access to economic resources (Alesina et al., 2016) as well as a form of discrimination (Heijmans, 2001; Yamamura, 2015) underlying higher vulnerability to climate-related impacts (Schleussner et al., 2016). To proxy ethnic inequality, we rely on the Ethnic Power Relations (EPR) database by Vogt et al. (2015), which provides country-specific information on the size of ethnic groups (relative to overall population) and on the assignment of each groups to a category depending on their power status, namely: discriminated, dominant, irrelevant, junior partner, monopoly, powerless, self-exclusion, senior partner or state collapse.

For the purposes of the analysis, we compute a measure of ethnic inequality representing the cumulative size of the discriminated ethnic groups with respect to total population in a given country and year.

Table 1 reports the acronyms for all variables used in results, the unit measure, the original sources and main statistics.

4. Empirical strategy

According to the framework of Section 2, damages due to natural disasters will be, ceteris paribus, harsher in unequal societies relative to more equal ones. Further, damages due to a natural disaster lead, everything else being equal, to increasing inequality. We operationalise the empirical estimation of these mutual effects by means of a system of simultaneous equations in Hypothesis 3. In the proposed model the dependent variable of one equation enters the other equation as explanatory variable. Since the error terms of the two equations are correlated, a standard OLS estimator does not satisfy the condition of independence of errors. Zellner and Theil (1962) posit that the adoption of a Three-Stage Least Square (3SLS) estimator ensures that independence conditions are not violated. This is a combination of the Two Stages Least Square (2SLS) and the Seemingly Unrelated Regressions Estimator (SURE), and it is recommended if cross-section correlation is suspected (Belsley, 1988). Appendix A.2 provides a thorough comparison of alternative estimation strategies between the proposed system approach and single-equation estimators such as OLS, instrumental variables (IV), and a quantile regression. Correlation statistics are also reported in Table A1.

The estimation procedure follows three steps. In the first, each endogenous variable is regressed on all exogenous variables to obtain instrumented values. In the second step, the instrumented values are used in place of the endogenous variables to estimate with an OLS the dependent variables of the model, equation by equation. This yields consistent estimates. The first two steps are the same as with 2SLS and SURE. However, 3SLS goes further by estimating simultaneously all coefficients of the entire model by Generalized Least Square (GLS) based on the variance–covariance matrix of disturbances, which is estimated by 2SLS. The variance–covariance matrix is the same used in SURE and ensures a greater efficiency of estimates compared to 2SLS.

For the use of 3SLS, the system must meet the identification condition, according to which the number of excluded exogenous variables is greater than or equal to the number of included endogenous variables:

$$m_i \leq (K - k_i) \tag{1}$$

where m_i is the number of endogenous variables of the model; K is the sum of the number of exogenous variables in all equations (k_i) and the number of excluded exogenous variables (instruments) in all equations. In our case, in addition to the dependent variables of our two main equations (namely, *HIT* and *Gini*), we also consider GDP per capita, the HDI in all different forms and all measures of adaptation supply (public expenditures, investments and infrastructures) as endogenous.

The debate over the relationship between GDP per capita and income inequality and their mutual causality has been widely debated. While

Table 1
Descriptive statistics and data sources.

Variable acronym	Unit measure	Obs	Mean	Std. Dev.	Min	Max	Source
Dependent variables							
HIT i,t	No. death toll + affected normalised by previous year population	4,023	0.01	0.06	0	1.07	EM-DAT and WDI
D_HIT i,t		4,023	0.01	0.05	0	0.91	EM-DAT and WDI
W_HIT i,t		4,023	0.01	0.04	0	1.07	EM-DAT and WDI
Gini i,t	Index	4,023	38.43	7.77	20.7	62.5	SWIID
Explanatory variables							
Socioeconomic resilience							
GDP per capita i,t	Ln (USD per hab.)	3,996	8.99	1.21	5.87	11.77	WDI
HDI i,t	Index	4,023	0.66	0.17	0.19	0.95	UNDP
GHDI i,t	Index	3,888	0.65	0.13	0.22	1.10	UNDP and WDI
NHDI i,t	Index	4,023	0.67	0.16	0.16	0.95	UNDP
GNHDI i,t	Index	3,888	0.66	0.13	0.23	1.07	UNDP and WDI
Public exp. i,t	% of GDP	4,023	15.69	6.06	0.91	47.19	WDI
Public inv. i,t	% of GDP	3,943	3.57	3.43	0.00	39.62	WDI
Disasters frequency							
No. disasters i,t	Number	4,023	1.82	3.47	0.00	34.00	EM-DAT
No. dry disasters i,t	Number	4,023	0.28	0.69	0.00	10.00	EM-DAT
No. wet disasters i,t	Number	4,023	1.54	3.12	0.00	32.00	EM-DAT
Stock disasters i,t	Number	4,023	24.05	50.78	0.00	629.00	EM-DAT
Stock dry disasters i,t	Number	4,023	3.76	7.51	0.00	107.00	EM-DAT
Stock wet disasters i,t	Number	4,023	20.29	44.61	0.00	537.00	EM-DAT
Geographical controls							
Rural population i,t	% of population	4,023	44.60	22.93	0.00	93.71	WDI
El Niño t	Dummy	4,023	0.26	0.44	0.00	1.00	NOAA
La Niña t	Dummy	4,023	0.30	0.46	0.00	1.00	NOAA
Land Area i	Squared km	3,988	8.01E + 05	2.07E + 06	3.20E + 02	1.64E + 07	WDI
Additional covariates for inequality							
Inst. quality i,t	Index	4,023	0.49	0.27	0.01	1.00	WGI
Ethnic marg. i,t	Index	3,888	0.03	0.09	0.00	0.84	EPR
Exogenous instruments							
Value added in agr. i,t	% of GDP	4,023	13.83	12.74	0.02	62.36	WDI
Dist. from Equator i	Km	4,023	3,072.08	1,950.38	65.23	7,644.67	WorldMap

some deem a certain level of inequality favourable for economic growth (Kaldor, 1956; Lewis, 1954), others consider it as a hindrance (Alesina and Rodrik, 1994; Easterly, 2007). Recent contributions question the prevalence of one direction over the other and advocate that wealth and equality in income distribution are two sides of the same coin, especially in less developed countries (Kuznets, 1955; Ranis et al., 2000). This however raises endogeneity concerns. Morevoer, public provision of goods and services to citizens may also suffer from endogeneity due to reverse causality since the share and composition of public budget depend on how income is distributed across voters. As suggested by Ferreira (2001), if political power is not equally distributed, public policies will likely support the advantaged groups, or the highest percentiles of the distribution, thus giving way to a self-sustained high-inequality trap.

We believe similar endogeneity issues may affect the relations of these covariates with physical damages from natural disasters. On the one hand, GDP per capita determines the affordability of effective prevention measures against natural disasters, thus affecting the number of people hit. On the other hand, in the event of a natural disaster the physical damages force unanticipated health costs, in turn affecting the GDP per capita. Similarly, the size of public budget devoted to restructuring or avoiding damages from hazards, as well as to health purposes in the aftermath of a disaster, is typically affected by natural disasters.

A common practice in empirical research is to employ lagged values as instruments for endogenous variables. Nonetheless, this would not suffice to address endogeneity issues in our case because damages due to extreme events are cumulative and GDP and public expenditures are unlikely to be independent from the impact of disasters. In view of this, we introduce two exogenous variables as time-variant regressors and country fixed effects as time-invariant instruments.

The first is the distance from the Equator which was first related to differential levels of development by Kamarck (1976). The adverse climatic and geographical conditions affecting countries in the tropics hinder economic development. Distance from the Equator was employed by Theil and Finke (1983) as instruments for GDP, while it was extended to the other dimensions of human development by Ram (1997). We compute the great-circle distances from the Equator in km based on the Haversine formula taking the centroid of each country based on latitude and longitude available in the Harvard WorldMap open-source database.

The second exogenous variable concerns public budget composition. A widely accepted instrument is the structure of the economy represented by the share of value added in agriculture as percentage of GDP (Haile and Niño-Zarazúa, 2018; Tanzi, 1992). Indeed, in countries relying on the agriculture sector raising taxes is more difficult, affecting in this way the optimal allocation of public expenditure. Finally, the use of country fixed effects as exogenous instruments allows controlling for heteroskedasticity in the error term while maintaining time-invariant variables in the two main equations. All explanatory variables potentially affected by endogeneity have been tested with a Sargan-test applied to a linear model for each equation (Baum et al., 2003).

To test formally the three hypotheses, we estimate the following system of equations:

$$HIT_{i,t} = \alpha_0 + \beta_1 Gini_{i,t} + X^{SE}_{i,t-1}\beta_{SE} + X^{PB}_{i,t-1}\beta_{PB} + \beta_4 D_{i,t-p} + X^{OC}_{i,t-1}\beta_{OC} + \delta_i + \eta_t + \varepsilon_{i,t} \tag{2}$$

$$Gini_{i,t} = \gamma_0 + \delta_1 HIT_{i,t} + X^{SE}_{i,t-1}\delta_{SE} + X^{SN}_{i,t-1}\delta_{SN} + \delta_i + \eta_t + \upsilon_{i,t} \tag{3}$$

where $HIT_{i,t}$is the number of people hit by natural disasters normalized by i^{th} country's population of the previous year; $Gini_{i,t}$ is Gini index; $X^{SE}_{i,t-1}$ is the set of socioeconomic variables representing the adaptation demand (GDP per capita and the different HDI computations); $X^{PB}_{i,t-1}$ is the set of covariates describing the composition of the public budget related to the adaptation supply; $D_{i,t-p}$ represents the different way we control for the impact associated to the number of disasters, experienced by country i in year t or in the past years according to the cumulative impact hypothesis; $X^{OC}_{i,t-1}$ is the set of controls related to country profile (land cover and the share of rural population), surface area of country i. In eq. (3) also includes a set of variables that capture the impact of social norms $X^{SN}_{i,t-1}$ represented here by the quality of institutions and the marginalisation degree of ethnic groups. Also in the model are time-invariant controls, δ_i, and potential effects that are valid across all statistical units but are specific to selected years, η_t. The intercepts $\alpha_0$and γ_0 are included since country fixed effects are treated as instrumental variables and not directly included among the explanatory variables. Finally, $\varepsilon_{i,t}$ and $\upsilon_{i,t}$ are the corrected uncorrelated error terms.

The additional controls δ_i and η_t refer to geographical and climatic factors that may be at root of natural disasters independent from other time-variant country features. The geographic effect is accounted for by continental dummies that capture the relatively higher exposure of a continent over the benchmark (that is Europe), all else being equal. Given that we use the distance from the Equator as instrumental variable, the variance in disaster risk related to the specific global geographical zone (mainly associated to the relative latitude) to which each country belongs is already captured. To control for climatic effects we use two variables that represent the years in which El Niño or La Niña prevail, respectively. Given that in some years neither El Niño nor La Niña prevail, both variables can be included as year fixed effects with no concerns of multicollinearity. When included, these two variables replace year-specific fixed effects whose coefficients are not reported.

Finally, we control for potentially divergent impacts due to different types of disasters by splitting the dependent variable into the number of people hit in consequence of dry disasters (*D_HIT*) or wet disasters (*W_HIT*). General estimation fit is controlled with the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) statistics, where the latter is penalised with respect to the former due to the number of parameters. Multicollinearity is tested with the Variance Inflation Factor (VIF) applied to each equation of the system, where the cut-off value as a rule of thumb for potential collinearity bias is 5.

5. Results

The baseline regressions include eight models to test the drivers of magnitude of disasters in the first equation (Table 2a) and of inequality (Table 2b). In general, the two main dependent variables, *Gini* in the disaster equation and *HIT* in the inequality equation, are robust in all specifications, with positive and highly significant coefficients that

Table 2a
Baseline models for testing Hypotheses 1–2-3 (Dependent variable: Normalised Total of Number of persons hit).

Disaster eq. (2)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini Index i,t	0.004***	0.004***	0.004***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GDP per capita i,t-1	−0.005**	−0.005***	−0.004**	−0.001	−0.002		−0.002	−0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)
NHDI i,t-1	0.094***	0.092***	0.122***					
	(0.01)	(0.01)	(0.04)					
NHDI_sq i,t-1			−0.026					
			(0.03)					
GNHDI i,t-1				0.196***	0.159***		0.161***	0.163***
				(0.06)	(0.06)		(0.06)	(0.06)
GNHDI_sq i,t-1				−0.112**	−0.088*		−0.089*	−0.090**
				(0.05)	(0.05)		(0.05)	(0.05)
GHDI i,t-1						0.112**		
						(0.05)		
GHDI_sq i,t-1						−0.066		
						(0.04)		
Public exp. i,t-1	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Public exp_sq i,t-1		−0.000						
		(0.00)						
Public inv. i,t-1					−0.001***	−0.001*	−0.001***	−0.001***
					(0.00)	(0.00)	(0.00)	(0.00)
No. disasters i,t	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		
No. disasters i,t-1							0.001***	
							(0.00)	
Stock disasters i,t-1								0.000***
								(0.00)
Land area i	−0.000	−0.000	−0.000	−0.000*	−0.000*	−0.000	−0.000	−0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Rur. pop. i,t	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Const.	−0.172***	−0.176***	−0.179***	−0.216***	−0.166***	−0.158***	−0.174***	−0.170***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes		Yes
Chi^2	1030.18	1029.19	1018.10	1023.25	788.95	648.73	798.54	768.44
RMSE	0.06	0.06	0.06	0.06	0.06	0.05	0.06	0.06
Mean VIF	2.74	2.74	2.74	2.34	2.07	2.18	2.07	2.06

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2b
Baseline models for testing Hypotheses 1–2-3 (Dependent variable: Gini index).

Inequality eq. (3)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HIT i,t	95.336***	94.788***	94.654***	94.081***	81.370***	68.520***	88.952***	87.851***
	(5.82)	(5.82)	(5.82)	(5.89)	(6.09)	(6.03)	(6.30)	(6.29)
GDP per capita i,t-1	1.492***	1.494***	1.478***	1.424***	1.264***		1.282***	1.280***
	(0.23)	(0.23)	(0.23)	(0.23)	(0.23)		(0.23)	(0.23)
NHDI i,t-1	−26.023***	−25.986***	−26.092***	−24.601***	−23.992***		−23.734***	−23.796***
	(1.66)	(1.66)	(1.66)	(1.60)	(1.61)		(1.61)	(1.61)
HDI i,t-1						−16.012***		
						(1.14)		
Public exp. i,t-1	−0.124***	−0.123***	−0.125***	−0.180***	−0.208***	−0.201***	−0.210***	−0.210***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Inst. quality i,t	−2.230***	−2.302***	−2.122***	−2.100***	−2.038***	−0.741	−1.980***	−1.968***
	(0.69)	(0.70)	(0.71)	(0.70)	(0.70)	(0.69)	(0.70)	(0.70)
Ethnic marg. i,t	0.439	0.515	0.502	1.148	2.415*	3.932***	2.419*	2.403*
	(1.30)	(1.30)	(1.31)	(1.34)	(1.34)	(1.34)	(1.33)	(1.34)
Const.	43.149***	43.121***	43.276***	43.690***	45.223***	50.680***	44.825***	44.885***
	(1.46)	(1.46)	(1.47)	(1.46)	(1.45)	(0.83)	(1.46)	(1.46)
Chi^2	1380.17	1378.51	1376.59	1356.46	1338.10	1253.93	1335.59	1337.66
RMSE	8.33	8.31	8.31	8.34	7.75	7.49	7.97	7.94
Mean VIF	2.59	2.59	2.59	2.59	2.59	1.61	2.59	2.59
No. Observations	3544	3544	3544	3469	3419	3444	3419	3419
AIC	10,080	10,109	10,138	10,163	10,366	11,000	10,111	10,195
BIC	10,469	10,504	10,533	10,556	10,765	11,387	10,510	10,594

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

jointly confirm the three hypotheses of the present paper. In particular, an increase in inequality is a positive predictor of the number of people affected by natural disasters. We interpret this as an outcome of unequal access to precaution and prevention measures as well as to health services in the aftermath of an event, as per H1. To quantify the effect, on average in the eight models reported in Table 2a, a 1% increase in the Gini index in a country at the 75th percentile corresponds to 3.7% more people hit by natural disasters than in a country at the 25th percentile. Accordingly, inequality *per se* causes a relative increase in impacts and damages provoked by disasters. Further, the positive sign of *HIT* in the inequality equation corroborates H2. In this case, an increase in the number of people affected by disasters entails a substantial rise of inequality, with the coefficient of *HIT* ranging between 68.5 in model 6 to 95.3 in model 1 that includes only base controls. The interquartile range on average is 17.5%, revealing that people living in places with higher exposure risks to damages might also suffer from further inequality.

Looking specifically at the four main dimensions, our preferred measure of adaptation demand (GDP per capita) is, as expected, negative but statistically significant only in the first two specifications. On the other hand, the human development level (NHDI) is a positive predictor of higher exposure to risk. Given this counterintuitive result, we explore the possibility of non-linearities due to the adoption of a broader development measure along with the well-established Environmental Kuznets Curve (EKC) approach (Costantini and Monni, 2008; Hussain and Dey, 2021; Sinha Babu and Datta, 2013). The addition of the quadratic term of the simple Human Development Index (*NHDI_sq*) in model (3) does not affect our results. Conversely, along with recent findings by Chowdhury et al. (2021) and Paudel and Ryu (2018), when we control for gender equality (*GNHDI*) in access to basic *opportunities* (i.e., education, health, and access to the labour market) the quadratic form is negative and significant (models 4–5), thus indicating an inverted U-shaped relation between the development level and the magnitude of impacts. Thereby, societies at early stages of development are relatively more exposed to damages due to lower availability of technologies, infrastructure resilience and prevention measures. Only countries above a human capabilities threshold and wherein women are guaranteed equal opportunities are less affected by disasters. In some countries, gendered differences in vulnerability may be further aggravated by cultural or religious factors that prevent women to evacuate or run for their life in the absence of the male head of the family (Sultana, 2014). On average, such a threshold corresponds to a gender-corrected development index of about 0.81, which is the score of all developed economies and of Azerbaijan, Barbados, Bhutan, Fiji, Kyrgyzstan, Mongolia, Qatar, Tajikistan, Vietnam (The average threshold is computed on coefficients in all estimations with the quadratic form of GNHDI, including those reported in Table 3a). In these instances, gender balance increases country ranks significantly compared to the simple NHDI. Further, the Gini index is close or below average and they often experience above average number of disasters. Model 6 of Table 2a reports the estimation with the complete HDI corrected with the gender bias, but the quadratic form is not significant. The inclusion of the GDP per capita dimension into the aggregated index reduces the explanatory power of the models since the economic adaptation capacity is mixed up with the dimensions related to access to resources in a capability approach.

Looking at the second group of variables that capture resilience supply, we observe that the share of public consumption expenditure on GDP (*Public* exp) is positively associated with a higher number of persons affected by damages. In this case, a non-linear specification as suggested by Martins and Veiga (2014) does not suffice for the mere increase of the relevant coefficient would capture the governments' propensity towards public spending but not its composition. To illustrate, large projects aimed at improving adaptation may simply transfer risk across individuals (Fordham, 1999; Kallis, 2008; See and Wilmsen, 2020), especially when strong interventions - i.e., structural engineering interventions as for instance the construction of dams - are preferred over soft ones - i.e., economic policy or ecological restoration interventions (D'Alisa and Kallis, 2016). Following public choice theory, such a positive relation would imply that in the aftermath of a natural disaster governments allocate large shares of the public budget to recovery, thus increasing the potential for corruption and rent-seeking behaviour (Yamamura, 2014), which would ultimately undermine the effectiveness of public spending for the purpose of preventing damages from further disasters. To capture the impact of the composition of public expenditure, we add a variable measuring the investment expenditures in nonfinancial assets (*Public inv*), which turns out to be significantly and negatively related to the magnitude of impacts.

The panel structure of the database allows capturing intertemporal effects in the disaster equation by including the number of prior events occurred both in the short and long-term. Results in models 7 and 8 indicate that the number of people hit by current disasters is higher if the

Table 3a
Climatic and geographical controls for different type of disasters (Dependent variable: Number of persons hit normalised).

Disaster eq. (2)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All Dis.	All Dis.	All Dis.	Dry Dis.	Dry Dis.	Wet Dis.	Wet Dis.	Wet Dis.	Wet Dis.	Wet Dis.
Gini i,t	0.003***	0.003***	0.003***	0.000*	0.001***	0.002***	0.002***	0.002***	0.002***	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	
Gini i,t-1										0.000**
										(0.00)
GDP per capita i,t-1	−0.002	−0.002	−0.002	0.000	0.000	−0.002*	−0.002*	−0.002*	−0.002*	−0.003**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
GNHDI i,t-1	0.178***	0.180***	0.184***	0.117**	0.108**	0.082**	0.086***	0.088***	0.072**	0.027
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
GNHDI_sq i,t-1	−0.118**	−0.120**	−0.125***	−0.093**	−0.085**	−0.045	−0.048*	−0.052*	−0.038	−0.013
	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Public exp. i,t-1	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.000**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Public inv. i,t-1	−0.001*	−0.001**	−0.001**	−0.000	−0.000	−0.000**	−0.000**	−0.000***	−0.000***	−0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
No. Disasters i,t	0.002***			0.014***		0.002***				
	(0.00)			(0.00)		(0.00)				
No. Disasters i,t-1		0.001***			−0.001		0.001***			
		(0.00)			(0.00)		(0.00)			
Stock Disasters i,t-1			0.000***					0.000***	0.000***	0.001***
			(0.00)					(0.00)	(0.00)	(0.00)
Interaction GDP-Dis i,t-1									−0.000***	−0.000***
									(0.00)	(0.00)
Land Area i	−0.000*	−0.000	−0.000	−0.000***	0.000	−0.000**	−0.000	−0.000	−0.000	−0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Rur. Pop. i,t	0.000***	0.000***	0.000***	0.000***	0.000***	0.000*	0.000**	0.000**	0.000*	0.000***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
El Niño t	0.003	0.003	0.003	0.002	0.002	0.001	0.001	0.001	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
La Niña t	0.004*	0.004*	0.004**	0.000	0.000	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Const.	−0.172***	−0.177***	−0.173***	−0.073***	−0.081***	−0.092***	−0.095***	−0.094***	−0.093***	−0.004
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Continent dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	No	No	No	No	No	No	No	No	No	No
Chi^2	784.36	796.99	773.48	271.74	161.73	907.32	893.84	886.32	896.52	249.92
RMSE	0.06	0.06	0.06	0.04	0.04	0.03	0.03	0.03	0.03	0.03
Mean VIF	1.89	1.93	1.93	1.85	1.89	1.88	1.92	1.91	19.8	19.8

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

country is persistently exposed to climate-related hazards. This validates H3 about the existence of a vulnerability-disaster trap as there is an additional cumulativeness effect together with the short-term higher frequency in number of events as controlled in models 1–6. Last but not least, even after the addition of controls for geographical features, our results confirm that countries with higher shares of rural population are, ceteris paribus, more exposed to high impacts on human activities.

Turning to the inequality equation (Table 2b), we adopt the same specification for the GDP per capita and the NHDI as for the disaster equation, both treated as endogenous. The combination of two effects emerges clearly. On the one hand, the coefficient of the pure impact of GDP per capita growth is positive and significant, thus indicating an increase in inequality. On the other hand, more diffused access to basic needs – such as education and health – substantially improves the equality in income distribution. These two effects are well-grounded in the argument, grounded in the seminal work by Kuznets (1955), that a rapid increase in GDP per capita is associated with an increase in inequality, especially at early stages of development. At the same time, appropriate investments in human capital and well-being may correct for inequality (Brueckner et al.; 2015). In our estimates the effect of GDP is the smallest, compared to that of NHDI, thus suggesting that the role of entitlements along with a capability approach more than compensate for the negative impact due to GDP growth (Ranis et al., 2000). This is further confirmed by estimation 7 of Table 2b where the GDP per capita is included in a complete HDI measure, with negative coefficient but lower in absolute term relative to the NHDI.

Moreover, the negative and statistically significant coefficient of the variable Inst. *quality*, which works in the same direction as *NHDI*, confirms the importance of quality of institutions in the relation between economic growth and inequality. Indeed, corrupted and/or inefficient governments may misallocate resources in a way that benefits small groups of privileged voters who have a vested interest in restricting access to improved well-being for the population at large (Gyimah-Brempong, 2002).

Finally, horizontal inequality captured by the size of marginalized ethnic groups (*Ethnic marg*) negatively impacts income distribution, in line with prior empirical literature (see i.e., Imai et al., 2011 on Vietnam). In this case the statistical significance improves after adding controls for the adaptation deficit in the disaster equation. Here, contrary to the disaster equation, the effect of public expenditure on inequality is robustly negative in all specifications. This implies that an increase in the share of public expenditure has positive redistributive effects independently on how resources are spent.

Tables 3a-3b contain the extension of the baseline analysis after the addition of specific controls for geographic and climatic effects in the disaster equation (models 1–3), by splitting the number of people hit between dry (models 4–5) and wet disasters (models 6–7), and by including a dynamic endogenous effect by lagging the variables of interest for wet events (models 8–10).

The main results are robust to these additions when all disasters are pooled together. As regards climatic controls, *El Niño* has no significant effect on the number of people hit by natural disasters, while *La Niña* has a positive effect especially for wet disasters. Coherent with the atmospheric oscillations associated to La Niña, in the case of dry disasters no effect is found. Even after the addition of geographic controls (*Land Area*, *Rur Pop*), specifications (1–3) indicate that continents more

Table 3b
Climatic and geographical controls for different type of disasters (Dependent variable: Gini index).

Inequality eq. (3)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All Dis.	All Dis.	All Dis.	Dry Dis.	Dry Dis.	Wet Dis.	Wet Dis.	Wet Dis.	Wet Dis.	Wet Dis.
HIT i,t	78.113***	85.251***	83.924***							
	(6.13)	(6.35)	(6.33)							
D_HIT i,t				20.601***	40.003***					
				(7.50)	(9.53)					
W_HIT i,t						140.515***	151.450***	151.737***	150.014***	
						(9.38)	(9.54)	(9.53)	(9.55)	
W_HIT i,t-1										12.950***
										(3.60)
GDP per capita i,t-1	1.280***	1.308***	1.311***	0.818***	0.868***	1.284***	1.311***	1.318***	1.322***	0.822***
	(0.23)	(0.23)	(0.23)	(0.22)	(0.22)	(0.23)	(0.23)	(0.23)	(0.23)	(0.22)
HDI i,t-1	−24.917***	−24.876***	−24.968***	−24.355***	−24.034***	−27.345***	−27.509***	−27.591***	−27.514***	−24.977***
	(1.62)	(1.63)	(1.63)	(1.58)	(1.59)	(1.64)	(1.64)	(1.64)	(1.64)	(1.57)
Public exp. i,t-1	−0.208***	−0.210***	−0.210***	−0.209***	−0.214***	−0.176***	−0.175***	−0.176***	−0.176***	−0.206***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
Inst. quality i,t	−1.708**	−1.597**	−1.573**	−2.050***	−1.989***	−1.542**	−1.447**	−1.379**	−1.457**	−2.015***
	(0.70)	(0.70)	(0.70)	(0.71)	(0.71)	(0.70)	(0.70)	(0.70)	(0.70)	(0.70)
Ethnic marg. i,t	2.067	1.945	1.920	2.547*	2.469*	2.180	2.119	2.045	2.102	2.738**
	(1.35)	(1.35)	(1.35)	(1.36)	(1.36)	(1.34)	(1.34)	(1.34)	(1.34)	(1.36)
Const.	45.524***	45.119***	45.203***	50.163***	49.458***	46.524***	46.216***	46.269***	46.290***	50.473***
	(1.43)	(1.45)	(1.44)	(1.34)	(1.37)	(1.40)	(1.40)	(1.40)	(1.40)	(1.32)
Chi^2	1336.98	1337.22	1338.38	1318.97	1316.39	1376.13	1391.83	1393.27	1387.52	1338.30
RMSE	7.66	7.87	7.83	6.65	6.81	7.66	7.84	7.85	7.82	6.58
Mean VIF	2.59	2.59	2.59	2.59	2.59	2.59	2.59	2.59	2.59	2.59
No. Observations	3419	3419	3419	3419	3419	3419	3419	3419	3419	3419
AIC	10,410	10,158	10,238	10,638	10,600	6401	6189	6195	6219	8456
BIC	10,705	10,453	10,532	10,926	10,889	6689	6478	6484	6514	8751

Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

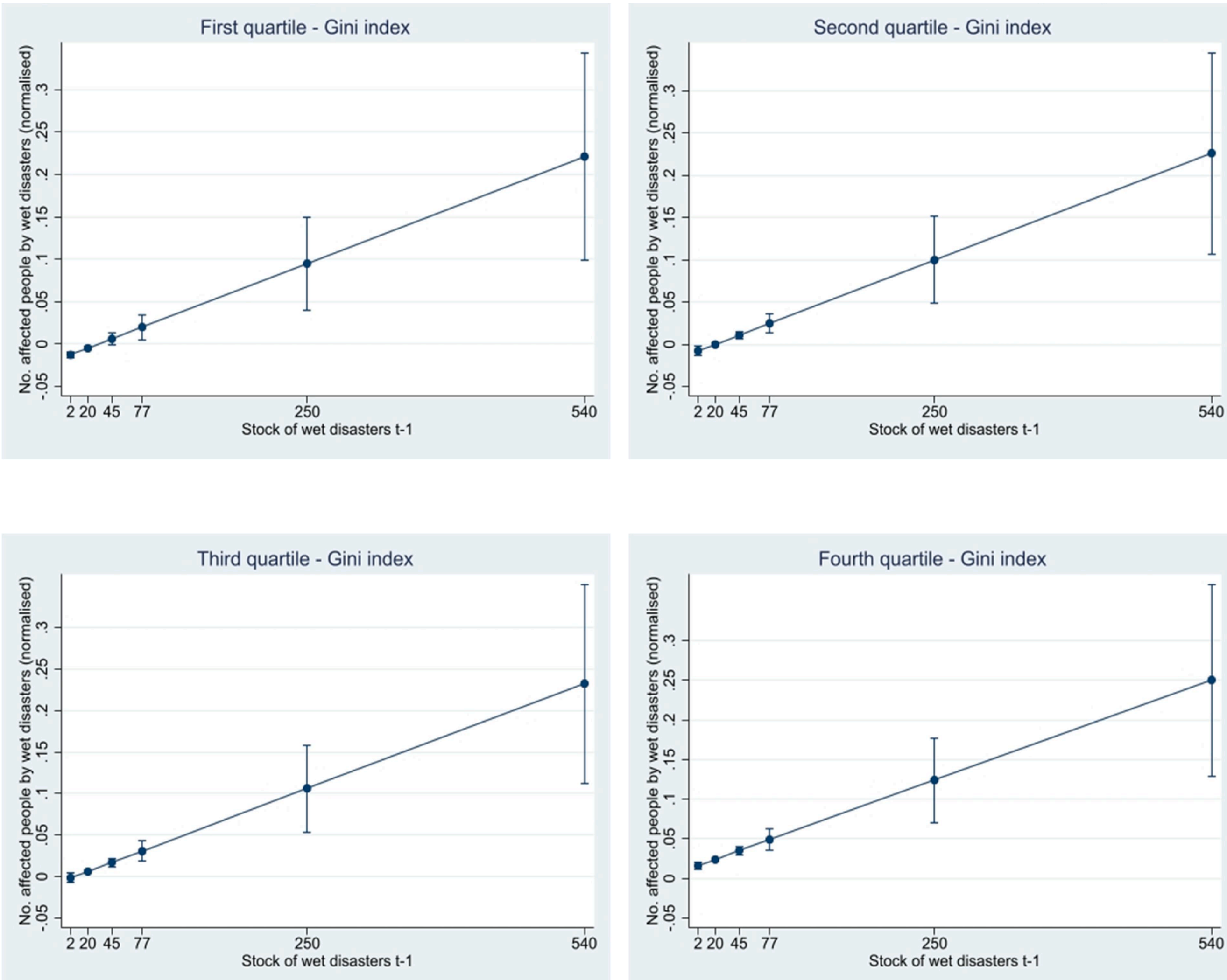
exposed to La Niña are also those where the number of people hit by natural disasters is higher.

When distinguishing between typologies of disasters, we find that the effect of inequality on the number of people affected is slightly higher in case of wet disasters relative to dry disasters (Table 3a, models 4–7). Further, when a higher number of people are affected by wet disasters, the effect on income inequality is much higher than in the case of dry disasters (Table 3b). This implies that countries under strain from repeated floods and storms struggle to escape the vulnerability-disaster trap as exposure, in terms of number of persons hit by wet disasters, is on average higher. Given that the livelihood of low-income households in developing countries depends on agriculture, resilience is necessarily lower in front of repeated shocks that destroy production capacity, even more when preventive measures are scarce or lacking altogether.

Furthermore, results for wet disasters exhibit three peculiarities. First, marginalisation in ethnic groups (*Ethnic marg*) affects income distribution in the event of frequent and repeated wet disasters (Table 3b). This resonates with prior evidence that the burden of disasters varies by race and ethnicity during emergency response, recovery and reconstruction (Fothergill et al., 1999; Pham et al., 2020). By and large, poor ethnic minority communities reside in areas that are more difficult to protect from extreme events, especially floods, storms and typhoons. The other two peculiarities are to some extent complementary. In particular, the impact of past shocks (Table 3a, model 7) is statistically significant only for wet events while the cumulative effect of past disasters (*Stock Disasters*) and our measure of resilience (*GDP*) in the disaster equation are statistically significant after controlling for geographical and climate-related features. This implies that income level is a good proxy of a country's capacity to protect citizens from damages provoked by disasters in a dynamic perspective. In other words, given similar in frequency and magnitude of disasters, richer economies are more resilient in the face of damages relative to poorer countries. To check for non-linearities, we include an interaction term between income level and cumulative frequency of disasters (model 9), which turns out to be negative and statistically significant. This confirms that in the face of similar exposure to disasters, the relative extent of the damage is inversely correlated with the country's level of wealth. To capture the magnitude of such a non-linear effect, we compute the marginal effects based on partial derivatives for the specific covariate *Stock Wet Disasters i,t-1* applied to the disaster equation with four quartile inequality groups from model 9. Fig. 5 reports marginal impacts of the stock of past wet disasters on the number of people hit (normalised by number of inhabitants in the previous year) over three thresholds: first quartile Gini < 0.34; second quartile Gini in the range 0.34–38.5; third quartile Gini in the range 38.6–43.7; fourth quartile Gini > 43.7. Marginal effects are reported for main percentiles in the distribution of the stock of wet disasters, as shown in the horizontal axis of the four graphs (corresponding to the 25th, 75th, 90th, 95th, and 99th percentiles).

The first Gini quartile exhibits statistically significant marginal effects with no changes in sign only after the 90th percentile of prior disasters (around 45, Fig. 5, top left panel). The cumulative impact of repeated events yields a higher toll of affected people only in countries in the tail of the disaster distribution, namely Australia, Canada, France, Japan, and South Korea. On average, wealthier and more equitable societies exhibit higher resilience to disasters, and significant damages are concentrated in countries that suffer systematically events of frequency and magnitude that undermines future recovery capacity. On the other hand, the marginal cumulative impact of disasters in countries in the fourth Gini quartile (Fig. 5, bottom right panel) increases together with income inequality, meaning that the frequency of disasters affects poorer societies and that such an effect increases more than proportionally with income inequality. As Fig. 5 shows, the distance between margins at the 99th percentile of disaster stock is higher than the same distance computed across Gini quartiles for the 25th disaster stock percentile.

Lastly, we test for persistency in the vulnerability-disaster trap by estimating the system of equations with both dependent variables in the other equation as a covariate with one-year lag (models 10, Tables 3a and 3b). Once again, the three hypotheses are simultaneously confirmed. This indicates that the trap is a vicious cycle, with self-reinforcing mechanisms that should deserve careful consideration when designing and implementing adaptation and development strategies. This is especially the case for countries that are exposed to repeated



Source: authors' elaboration on estimates

Fig. 5. Predicted margins for W_HIT w.r.t. stock of wet disasters for different inequality levels *Source: authors' elaboration on estimates.*

events classified, like wet disasters, given their relative higher strength and diffusion of disruptive effects that are difficult to recover from in a short time before the following event.

6. Conclusions

The study of climate change-induced disasters is extremely complex. Disasters stem out the interaction of climatological, environmental and socioeconomic factors that our analysis shows to be highly interrelated under specific circumstances. Countries suffer differently the effect of natural disasters, and so do population and income groups within each country. Rapidly changing climate conditions are known to trigger extreme events, and are expected to become more frequent in the near future. The risk is that recurrent climate-related disasters may undermine the ability of a country to recover and to prepare for future events, thus ultimately exacerbating the vulnerability of exposed populations.

Our work adds to prior research by exploring empirically these complex associations in relation to natural disasters between 1992 and 2018. We find that countries with higher levels of inequality that have been affected more frequently by extreme climatic events may be trapped in a vicious cycle. If countries are unable to restore a fair distribution of income and resources, as well as broader access to precautionary measures and health services, increasingly frequent disasters will likely prevent the adoption of adaptation measures and, thus, further undermine resilience.

Our analysis calls for a broader understanding of natural disasters as the combination of climatic and socioeconomic factors. Such a view would ideally guide modelling of climate change impacts and would, also, inform policy to minimise the associated hazards. Adaptation mechanisms should keep pace with rapidly changing climate to consider floods, storms, droughts, etc. as natural events, and not as disasters. For this to be possible, policy makers should ideally strive to guarantee equitable access to precautionary and recovery measures.

CRediT authorship contribution statement

Federica Cappelli: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing - review & editing, Visualization. **Valeria Costantini:** Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft, Writing - review & editing, Visualization, Supervision, Funding acquisition. **Davide Consoli:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing - review & editing, Visualization, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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