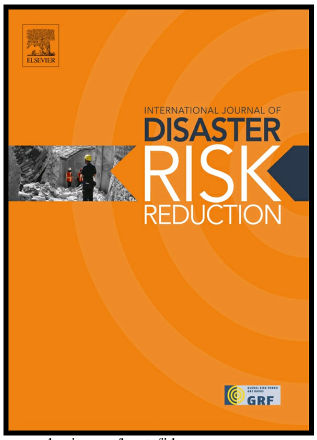


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# What causes nations to recover from disasters? An inquiry into the role of wealth, income inequality, and social welfare provisioning

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**Abstract:**

Disasters affect significant numbers of people in the poorest parts of the world. The main impediment to progress in reducing the extent of disaster outcomes appears to come from inabilities to address macro-economic drivers of vulnerability. This study examines the association between three key drivers of vulnerability, i.e. wealth/poverty, income inequality and the absence/presence of social welfare systems, and short-term and long-term disaster outcomes. Drawing on lengthy time-series data, we apply a data driven approach, focusing only on those countries that have experienced major natural or technological disasters, to generate new understanding of these drivers. Our study finds that in relation to natural hazards: less developed countries experience worse human impacts than more developed countries; developed countries suffer larger economic losses; countries with greater levels of income inequality have more people affected than in more equal countries; and social welfare (using both Sen's indexes and public social spending) in OECD countries appears to reduce the human impacts of disasters. We also conclude that the human impacts of natural disasters delay economic growth in poor countries. For the technological hazard-associated disasters, while there is no evidence that national wealth and income inequality determine human impacts, we find that larger human impacts in poor countries undermines economic growth. Our key finding is the unequivocal and central role of income inequality in shaping disaster outcomes. Future research and policy on disaster risk reduction has to acknowledge this 'elephant in the room'.

**Keywords:** natural disasters; technological disasters; national wealth; income inequality; social welfare

## 1. Introduction

Disasters impede development (Pelling et al. 2004; Foresight 2012; UNISDR 2009); the evidence is clear, but why is this the case? Theory suggests that disasters skew the process of development by imposing the greatest impact on the poorest and most marginalized members of society during disasters and in the recovery stage, especially those who live in countries with low wealth and high inequality. Moreover, empirical evidence is starting to indicate that people with subsistence livelihoods can become trapped in a cycle of poverty they cannot escape, and find their limited assets depleted in repeated hazards (Duncan et al. 2017; Enfors and Gordon 2008; Eriksen and Silva 2009). Social welfare provisioning appears to be crucial to supporting the poorest through disasters, although individual case-studies are showing a complex relationship between cash and food transfers and wellbeing (Sabates-Wheeler and Devereux 2010; Soares 2011). This paper examines the role of national wealth, income inequality and social welfare in shaping disaster outcomes (both natural and technological). If we are to achieve the United Nations' Sustainable Development Goals (SDGs) by 2030, action is needed to identify how to decouple the link between disasters and development (Pearson and Pelling 2015). This paper provides insight into the associations between these three key drivers of development vulnerability[1] and disaster outcomes, thereby highlighting areas for policy action.

Recognizing the damaging relationship between disasters and development, the Sendai Framework for Disaster Risk Reduction 2015-2030 advocates the need for improved understanding of disaster risk and the strengthening of disaster risk governance, as two of its four priorities (UNISDR 2015). Specifically, it calls for policies and practices for disaster risk management to be based on a multi-dimensional understanding of disaster risk taking into account: vulnerability, capacity, exposure of persons and assets, hazard characteristics and the environment, known as 'Priority 1'. It further calls for strengthening of disaster risk governance for prevention, mitigation, preparedness, response, recovery and rehabilitation is necessary, known as 'Priority 2'. These are not new goals. They have been widely cited as urgently needed (UNISDR 2009; IPCC 2012) and have been core priorities of the

[1] It is widely known that vulnerability is a complex concept and can be defined in many ways. However, taking into account that we are using country-level (macro) data and not people-level (micro) data, vulnerability in this paper refers to the characteristics of a country that influence its capacity to anticipate, cope with, resist and recover from the impact of a hazard.

UNISDR since the Yokohama agreement (UNISDR 1994). But they have not yet been achieved. These priorities come from theoretical work on disasters and development in the 1980s and 1990s that linked high levels of poverty, inequality and constraining economic structures with long-term and systemic vulnerability to hazards (Wisner et al. 2004). Wealth, inequality and provision of social welfare have each been linked to disaster outcomes individually through individual hazard-specific or location-specific research. What is missing is global or large-scale research on the drivers of disaster risk and disaster outcomes (Tierney and Oliver-Smith 2012). The absence of this research manifests as limited guidance on how national, regional and global governance can effectively manage disaster risk. We aim to fill this gap, by exploring whether pre-disaster levels of wealth, inequality and social protection have impacts on disaster outcomes. In other words, do countries with high welfare, low inequality and high provision of social welfare fare better after disasters than others? Our research takes these questions of associations between disaster outcomes and vulnerability further, by exploring the association between disaster outcomes and economic growth[2]. There is mixed evidence of a dampening effect of disasters on economic growth, with less-developed and developing countries appearing to experience worse effects than the developed world, possibly due to their reliance on agriculture, which is easily damaged during disasters (Anbarci, Escaleras, and Register 2005; Noy 2009).

Given the increasing availability of global data on disasters and development, we draw on this resource, using a data-driven approach, to try to untangle the complex associations between development and natural and technological disasters[3]. By focusing only on those countries which have experienced disasters (i.e. we do not consider countries that are affected by hazards but which do not experience severe impacts), we endeavour to draw out lessons on the key factors that are generating and impeding improvements in short-term and long-term disaster outcomes for both people and economic growth.



[2] It should be mentioned here that identifying the long-term impact of disasters can be difficult, this is due to the following: i) disasters often do not affect the entire economy (with the exception of small islands and states), but only localized areas; and ii) disasters tend to damage physical stocks of capital and human capital, but this can be offset by replacement capital during the recovery stage of disasters (Horwich 2000).

[3] In this paper, we follow the definition and classification of disasters considered in EM-DAT (2018). Using the EM-DAT definition, a disaster is a situation or event which overwhelms local capacity, necessitating a request at the national or international level for external assistance. It is an unforeseen and often sudden event that causes great damage, destruction and human suffering. We consider two types of disasters: a) natural disasters (i.e. geophysical, such as earthquakes, mass movement and volcanic activity; meteorological, such as extreme temperature, fog and storms; hydrological, such as floods, landslides and wave action; climatological, such as drought, glacial lake outbursts and wildfires; biological, such as epidemics, insect infestation and animal accident; and extra-terrestrial, such as impacts and space weather); and b) technological disasters (i.e. industrial accidents, such as chemical spills, collapses, explosions, fires, gas leaks, poisoning, radiation and oil spills; transport accidents, such as air, road, rail and water; and miscellaneous accidents, such as collapse, explosion and fire) (EM-DAT 2018).

Our specific aim is to identify the existence and nature of any association between macro drivers of socio-economic vulnerability and disaster outcomes for both people and economic growth at the global scale. The benefit of undertaking analysis at this scale is that we are able to identify the existence of associations between key variables that allow us to generalise, which previous small-scale research in this area has failed to deliver. To do this, we ask four questions: 1. Does national wealth influence the disaster outcomes (in terms of fatalities, numbers affected and economic damage) from both natural and technological hazards? 2. Does income inequality influence disaster outcomes from both natural and technological hazards? 3. Does the presence of social welfare programmes reduce the size of disaster outcomes from both natural and technological hazards? And finally, 4. Do disaster outcomes affect economic growth? This paper also attempts to find which of these factors are the most important and to compare natural with technological disasters.

To the best of our knowledge, this is the first study which examines the role of these factors simultaneously not only for natural disasters but also for technological disasters. We first use national wealth, income inequality and social welfare provisioning as independent variables, to see whether *ex-ante* policy instruments relating to economic, income and social protection generate greater or lesser returns than investments in *ex-post* response to disasters i.e. emergency assistance and relief (Sann et al. 2012). We then use the human and economic impacts of disaster outcomes as independent variables, to see whether policy interventions to reduce disaster risks could be used as *ex-ante* instruments to manage long-term economic growth in countries which are badly affected by disasters. The ultimate aim is to draw out some potentially useful policy recommendations designed to lower human and economic impacts from disasters and increase disaster resilience.

In the next section, we explore the literature on the relationships between national wealth, income inequality and social welfare and disaster outcomes, and the influence of disaster outcomes on economic growth. A set of hypotheses concerning these relationships has been formulated by combining the main results of the literature concerning this topic. In section 3, we present the data and variables used in the analysis, as well as the econometric specifications of the regression models used. Our results are presented in section 4, and we draw out the wider implications of the findings, and policy recommendations in section 5.

## 2. Disasters and development

Disasters affect significant numbers of people, especially in the poorest parts of the world. For example, in the Asia-Pacific region, in 2015, over 70 million people were affected by disasters, with over 16,000 fatalities. In India alone, using Government of India data, Ray-Bennett (2007) shows that between 1985 and 2001, each year across India approximately 1.6 million houses were partially damaged or completely destroyed and 35.4 million people were affected by disasters. However, disasters are more than events that cause death, injuries and destruction to a society. They are a human problem that should be viewed in the context of the economy and society (Cuny 1978; Cannon 1994). Disaster outcomes have the potential to derail the pursuit of the SDGs, which are a universal call to ensure that all people benefit from prosperity. Hence, there is a need for urgent action to address the socioeconomic drivers of disaster outcomes which reduce prosperity (Stern 2009). To do so, there are calls to develop integrative and holistic frameworks to systematize and assess vulnerability, risk and adaptation outlining key factors that need to be addressed when assessing vulnerability in the context of hazards (Birkmann et al. 2013; Cutter, Boruff, and Shirley 2012).

In this section, we explore the main arguments behind the factors that could manage risks and vulnerabilities, and, more specifically, we consider the key theorized factors of wealth, inequality and social policy. Three decades have passed since sociologists such as Bolin and Quarantelli highlighted the social and economic nature of disaster. There is now broad agreement that disasters occur at the intersection between a hazard and vulnerable people or places (Wisner et al. 2004). A rich body of literature exists on the causes of vulnerability, e.g. Cutter, Boruff and Shirley (2012), Birkmann et al. (2013), Adger (2006) and Eakin and Luers (2006), which theorise but do not evaluate the effects of wealth, inequality and social welfare on people and the economy in general. This section considers each of these three elements in turn.

A large body of small scale case-studies has explored the relationship between individual disasters and wealth (e.g. Cutter et al. 2006; Duncan et al. 2017), yet large-area and international comparative studies on the same topic are rare. One of the few studies to take a global comparative perspective (Ward and Shively 2017) highlights the relationship between frequent damaging disaster impacts and slower long-term economic development and wealth. They find that: i) low-income countries are significantly more at risk of climate-related disasters, even after controlling for exposure to climate hazards and other factors that may confound disaster reporting, and ii) higher income generally diminishes a country's social vulnerability to such events, resulting in lower levels of mortality and morbidity. They conclude that continued economic development may be a powerful tool for lessening social vulnerability to climate change. This paper advances the work of Ward and Shively by shedding light on the role of multiple, but key, drivers of vulnerability (i.e. wealth, income inequality and social welfare support) in disaster outcomes.

The damaging role of socioeconomic and income inequality has been demonstrated globally. Lack of knowledge of how to address the intractable problem of income inequality has acted as a barrier to progress on reducing disaster risk for decades. Case-studies which explicitly explore the relationship between inequality and disasters tend to focus on a specific hazard, or consider just one region or nation – limiting generalizability. For example, Ray-Bennett's (2009) work in India highlights the roles of caste, class and culture in shaping disaster outcomes in Odisha. She points to the fact that women, particularly those from the lowest caste, remain more likely to experience long-term and damaging impacts following disasters. Tierney (2006) looks at the social injustice issues associated with the Hurricane Katrina disaster in New Orleans in 2005, and highlights racial difference as a driver of unequal outcomes. Keerthiratne and Tol (2018), using similar methods to Bui et al. (2014), explore the relationship between natural disasters and income inequality in Sri Lanka, and find that natural disasters tend to more negatively affect agricultural incomes (agriculture tends to the main livelihood of the poorest in society). Jones et al. (2011) identified that unequal levels of support in post disaster recovery worsen prevalence of mental health issues in Mexico. In the United States, post hurricane evidence shows that after a disaster the highest rates of outmigration were found in the most deprived areas (Myers, Slack, and Singelmann 2008). The UN and World Bank provide many more localized examples (World Bank and United Nations 2010). These types of studies are slowly increasing in number, providing a richer understanding of the link between disasters and inequality at the local scale, but they are not contributing to our knowledge about the global setting (Yamamura 2015; Strömberg 2007).

Few analyses that exist at the global level that attempt to explain higher level relationships between income inequality and disaster outcomes. Using cross-country panel data, Strömberg (2007) examines whether income inequality is correlated with disaster-related deaths, while Yamamura (2015) examines how the occurrence of natural disasters has affected income inequality. The limitation of the empirical literature on this topic is all the more surprising in view of the theoretical importance of inequality reduction for disaster risk reduction. The analysis performed in this paper is an attempt to fill this significant gap in empirical studies of the associations between income inequality and disaster outcomes at a global level.

Social welfare policies and programmes have been developed, applied and tested to reduce social problems associated with hazards, especially in the less-developed and developing world, i.e. across Latin America, Africa and Asia (Slater 2011). The benefits from these programmes are well documented, such as the economic development and social welfare gains in NE Brazil from the Bolsa Familia programme (Lemos 2007), and the food security stabilization benefits of the Productive

Safety Net Programme in Ethiopia (Berhane et al. 2014). Yet, social welfare policies have also generated some cause for concern. Critics have pointed to the damaging impacts of food distribution systems on domestic food production, and noted that cash transfers can undermine local markets and create inflation or price distortions (Devereux and White 2010). It is therefore not only disasters themselves which can create lasting damage, but in some cases the social welfare policies put in place can create negative effects. Despite increasing interest in social welfare policy, little is known about the association between social welfare provisioning and short-term and long-term disaster outcomes. The World Bank provides annual updates on social welfare coverage and spending (World Bank 2018), and some studies have looked at trends in social welfare provisioning and poverty reduction. Fiszbein, Kanbur and Yemtsov (2014), for example, conclude that while social welfare keeps many people out of extreme poverty, there may be not sufficient budgetary resources for it to be an effective tool to deliver SDG goal of halving poverty in many low-income countries. At the household level, some work has been undertaken to examine the impacts of disasters on household welfare, see for example, Sann et al. (2012) who link social protection interventions in Cambodia to address the entitlement failure of poor and vulnerable people suffering from the impacts of flood and drought. This paper attempts to take forward the work on social welfare by analyzing the association between disaster impacts and social welfare provisioning around the globe.

What is increasingly clear is that disasters harm people in many ways, affecting not only their homes and livelihoods but also physical and mental health, which in turn affects economic growth. Health problems can affect people's ability to support their own families, function in society, and maintain full employment. For example, after a hydro-meteorological disaster in tropical developing countries there are frequently epidemics of malaria (Watson, Gayer, and Connolly 2007). Evidence is conclusive that there is a strong correlation between malaria and economic development (Sachs and Malaney 2002). After major disasters depression and post-traumatic stress disorder are common, affecting people's ability to get on with their lives and return to work (Munro et al. 2017). There is growing evidence of the health impacts of disasters in the developed world (Bell et al. 2017), but far less is known in the developing world. In combination, when many people are simultaneously affected, these factors all alter the present and future rates of economic growth. Therefore, this paper also assesses the human and economic impacts of disasters on economic growth.

## 3. Data and methods

### *3.1 Data and variables*

To better understand the drivers of disaster impacts, we draw on data reflecting the key drivers of vulnerability, i.e. measures of national wealth, inequality and the presence of social welfare programmes. In this paper, we obtain data and construct variables from five international databases. Data on disaster outcomes were obtained from the Emergency Events Database (EM-DAT)[4], which documents disaster outcomes by nation, disaster type since 1900 using a variety of metrics. EM-DAT is an unbalanced database, i.e. the number of data points available for different classes is different. The imbalance occurs because some countries may experience multiple disasters in the same year while others experience none. There are two further reasons for imbalance: a) for any country in a given year there has been a disaster but it does not satisfy the CRED criteria, or b) for any country in a given year there has been a disaster that satisfies the CRED criteria but it has not been observed and documented in the dataset (especially before 1988). The set of data where country-year observations are not observed due to lack of documentation is likely to produce bias because it generates missing observations (Tselios and Tompkins 2017).

EM-DAT provides information on the human impact of disasters[5] and on the disaster-related economic damage[6] estimates. According to EM-DAT, the number of natural disasters rose between 1900 and 2000 and the number of technological disasters rose between 1900 and 2005 (Appendix

[4] EM-DAT contains data on the occurrence and effects of over 22,000 mass disasters in the world from 1900 to the present day, conforming to at least one of the following Centre for Research on the Epidemiology of Disasters (CRED) criteria: 10 or more people dead, 100 or more people affected, the declaration of a state of emergency and a call for international assistance (EM-DAT 2018).

[5] The human impact of disasters is measured a) by the number of total people affected, which includes the number of people injured (i.e. people suffering from physical injuries, trauma or an illness requiring immediate medical assistance as a direct result of a disaster), the number of people made homeless (i.e. people whose house is destroyed or heavily damaged and therefore need shelter after an event), and the number of people affected (i.e. people requiring immediate assistance during a period of emergency requiring basic survival needs such as food, water, shelter, sanitation and immediate medical assistance) (i.e. *total affected* = *injured* + *homeless* + *affected*); and b) by the number of people killed, which includes sum of the dead (i.e. people who lost their life because the event happened) and missing (people whose whereabouts since the disaster is unknown and who are presumed dead) (i.e. *total killed* = *deaths* + *missing*) (EM-DAT 2018). Hence, *human impact* = *total affected* + *total killed* = *injured* + *homeless* + *affected* + *deaths* + *missing*. We do not calculate the per-capita human impact of disasters because hazards, and therefore hazard-associated disasters, strike a local or regional part of a country and they rarely affect entire nations (Tselios and Tompkins 2017; Escaleras and Register 2012).

[6] The economic impact of disasters is measured by the value in mil. US$ at constant 2005 national prices of estimated damage to property, crops and livestock. This index measures the direct losses associated with a natural or technological hazard impact after an event, but it does not measure the indirect damage and longer-term macroeconomic effects (Pielke et al. 2003). Similar to human impact, we do not calculate the per-capita economic impact of disasters.

1). This increase is attributed to both societal change and economic development (Bouwer et al. 2007; Escaleras and Register 2012), and to improvements in data collection and reporting in EM-DAT (Guha-Sapir, Hargitt, and Hoyois 2004). The human and economic impact of natural and technological disasters varies significantly over time (Appendix 2). For example, total affected persons by natural disasters spiked in 2002, whereas for technological disasters it peaked in 1981; total deaths by natural disasters spiked in 1931, whereas total deaths by technological disasters spiked in 2002. Total economic damage from disasters spiked in 2011 for natural disasters and in 2010 for technological disasters. Since the variation in the observations on both disaster outcome variables is wide (i.e. the distribution is asymmetric and skewed), we take the natural logarithm (*ln*) of these variables, because most of the mass of the logarithmic transformation of these variables is nearly symmetrical.

Data on national wealth were obtained from the Penn World Table[7] (PWT) (Feenstra, Inklaar, and Timmer 2015). We use two proxies for national wealth: a) national output and b) national growth. We measure national output as the real GDP per capita at constant 2005 national prices in mil. US$ and national growth as the annual GDP per capita growth (short-term growth) and as the five-year GDP per capita growth (long-term growth). All these variables are in *ln* form. Moreover, the *ln* scale takes into account the scaling effect. For example, the *ln* of GDP per capita compacts (reduces) the variable scale of countries with high GDP per capita. Hence, it is a better approximation of national output that GDP per capita changes multiplicatively than that it changes additively, so analysis on *ln* scale is helpful.



The Standardized World Income Inequality Database (SWIID) provides comparable estimates of the Gini index[8] of net-income inequality, which is defined as inequality in equivalized (square root scale) household disposable (post-tax, post-transfer) income, using Luxembourg Income Study data as the standard, for 192 countries for as many years as possible from 1960 to the present (Solt 2016). The net-income inequality index is usually assumed as the best suited index (Solt 2016). Despite this, we also use the Gini index of market-income inequality, which measures the distribution of income before taxes (e.g. tax on wages, salaries, dividends, interest and rents) and transfers (e.g. publicly-

[7] PWT is a database with information on relative levels of income, output, input and productivity, covering 182 countries between 1950 and 2014.

[8] The Gini index or coefficient is the most popular measure of income inequality. It leverages a scale from 0 to 1 (or 100) to derive deviation from perfect income equality. This index satisfies the criteria of scale invariance (i.e. mean independence and population size independence) and the principle of transfers (i.e. the transfer of income from rich to poor reduces measured inequality), but it is not consistent with the welfare principle that income transfers are more consequential among the poor than among the rich (Firebaugh 2003; Cowell 1995). Moreover, the Gini index is sensitive to outliers (such as the very few wealthy individuals), because it is calculated using sample people at random.

provided in-kind transfers, such as public spending on education and health care). This is very important because countries differ widely with respect to the level of tax and transfers. In some countries, cash transfers are small in size but highly targeted to those in need (OECD 2012). Generally, tax and transfers reduce overall income inequality. Although market-income inequality takes into account taxes and transfers, it cannot be considered 'pre-government', because a wide range of non-redistributive government policies (e.g. public education) shape the income distribution (Solt 2016; Iversen and Stephens 2008). Generally, as the coverage and comparability of SWIID far exceed those of alternative datasets, the SWIID is better suited for broadly cross-national research on income inequality than other sources (Solt 2016).

Social welfare is a multidimensional concept and it is difficult to operationalize (Sen 1973). We use two proxies for social welfare: a) Amartya Sen's social welfare index (Sen 1974, 1976), in *ln* form, which can be considered as an output of social welfare, and b) the public social spending as a percentage of GDP, which can be considered as an input of social welfare.

Sen's social welfare index of a country is defined as *GDPpc(1-Gini)*, where *GDPpc* is the per-capita GDP of the country (source: PWT) and *Gini* is the Gini coefficient on income inequality within the country (source: SWIID). Hence, the higher the GDP per capita of a country and the lower the income inequality within this country, the higher the social welfare of the country. This index, therefore, considers not only the level of economic output of a country, but also how that output is distributed to their citizens (England 1998).[9] It is an 'objective' index and has the advantage that it is relatively free of the cultural and language problems that presumably bedevil questionnaire evidence on 'subjective' welfare, such as life satisfaction and happiness (Blanchflower and Oswald 2007; Rodríguez-Pose and Tselios 2015). Moreover, people use a variety of reference points from their own experiences, beliefs and social imprints to evaluate their current situation (Aslam and Corrado 2007; Fernandez and Kulik 1981), which means that measures of self-reported well-being are subject to the problem of adaptive preferences (Elster 1983; Sen 1999; Nussbaum 2000). Hence, self-reported well-being may be affected by the personality of the individual being surveyed or by the conditions of the place where he/she lives.

The public social spending represents financial flows controlled by General Government (different levels of government and social security funds), in the form of social insurance and social assistance

[9] Although Sen's social welfare index has been used in many empirical studies to proxy for social welfare, it is not without limitations which have to do with the broad concept of social welfare. Social welfare is not only about the level of economic output of a society (e.g. country) and how that output is distributed to their citizens, but it is also about the quality of life of the citizens. Social welfare encompasses not only income, but also education, culture, democracy, institutions, justice and security, among others.

payments. It has been obtained from the Organisation for Economic Co-operation and Development (OECD) social expenditure database (SOCX[10]). This indicator is available for 35 OECD countries[11] for the period 1990-2016.[12] Social spending was at a historical high (i.e. about 21 per cent of GDP) in 2016 in many OECD countries (OECD 2016). Nonetheless, there is some variety across OECD countries in public social spending. For example, differences in pension spending to some extent are related to differences in the age structure of populations, the number of senior citizens who have access to pensions and their payment rates, and the increase in public expenditure on health is related to the rising relative health prices and the cost of medical technology and to the increase in the proportion of the elderly population (OECD 2016). Economic trends affect social spending. For instance, public spending on labour market policies actually fell after the beginning of the global economic crisis in 2009 as spending on unemployment compensation declined after the crisis, the economic crisis has affected demand for affordable housing, and during the period of economic crisis fiscal space for housing support remained tight (OECD 2016).

Data on the control variables[13] were obtained from EM-DAT, PWT and The World Bank Data (WB)[14]. The control variables used in this paper were chosen after considering the existing literature on the determinants of disaster outcomes as well as the data availability (e.g. long time-series availability). The control variables are: a) the number of disasters in *ln* form (source: EM-DAT), which may capture the exposure of a country to disasters (Tselios and Tompkins 2017; Escaleras and Register 2012); b) the number of people engaged in millions in *ln* form (source: PWT), which is a proxy for the market-size effect (Vaillancourt and Haavisto 2016; Escaleras and Register 2012; Yamamura 2012); c) the

[10] SOCX was developed to serve a growing need for indicators of social policy and is based on the work of Adema, Fron and Ladaique (2011). This database includes reliable and internationally comparable statistics on public and (mandatory and voluntary) private social expenditure at the programme level. SOCX presents public and private benefits with a social purpose grouped along the following policy areas: old age, survivors, incapacity-related benefits, health, family, active labour market programmes, unemployment, housing and other social policy areas (OECD 2016).

[11] The 35 OECD countries are: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Republic of Korea, Latvia, Luxembourg, Mexico, The Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom and United States. Today, the number of OECD countries is 36, including Lithuania. These countries span the globe, from North and South America to Europe and Asia-Pacific. They include many of the world's most advanced countries, but also emerging countries like Mexico, Chile and Turkey (http://www.oecd.org/about/membersandpartners/).

[12] We do not measure the total net social spending as a percentage of GDP, which takes into account public and private social expenditure, and also includes the effect of direct taxes (income tax and social security contributions), indirect taxation of consumption on cash benefits as well as tax breaks for social purposes, because it is available only for 2001, 2003, 2005, 2007, 2009 and 2013.

[13] Control variables are variables that are not of primary interest (here, the primary interest variables are national wealth, income inequality and social welfare, which are independent variables) and constitute an extraneous factor whose influence is to be controlled or eliminated.

[14] https://data.worldbank.org/indicator

total factor productivity (tfp) at constant national prices (source: PWT), which is a proxy for the technological progress and innovation and it is an important factor because if new technology is adapted, it makes the buildings more efficient; d) the population density (i.e. people per square km of land area) in *ln* form (source: WB), which usually captures agglomeration effects (Vaillancourt and Haavisto 2016); and e) the population in the largest city (i.e. percentage of urban population), which is the percentage of a country's urban population living in that country's largest metropolitan area (source: WB), and is likely to represent the urban hierarchical structure of a country.[15] The control variables capture some countries' features and deal with some sources of heterogeneity, reducing omitted variable bias.

Table 1 reports the number of observations, the mean, the standard deviation, the minimum and the maximum value for the variables above the merged database. Both the human and the economic impact of natural disasters are higher than those of technological disasters. Unfortunately, EM-DAT provides the economic impact of technological disasters for only a limited number of events (116 out of 1,671). This limitation does not allow us to examine the influence of national wealth, income inequality and social welfare on the economic impact of technological disasters as well as the economic impact of these disasters on economic growth using econometric analysis. The Pearson correlation coefficient between the explanatory variables is not very high, apart from the coefficient between the net- and the market-income inequality, between the two proxies for Sen's index (*ln*), and between the GDP per capita (*ln*) and Sen's index (*ln*) (Appendix 3).



### *3.2 Econometric specifications*

We use the following econometric specification to examine the influence of national wealth, income inequality and social welfare on disaster outcomes:

$$lnDis_{it} = \beta_0 + \beta_1 lnGDPpc_{it} + \beta_2 \ln\left(\frac{GDPpc_{it}}{GDPpc_{it-1}}\right) + \beta_3 \ln\left(\frac{GDPpc_{it}}{GDPpc_{it-5}}\right) + \beta_4 IncIneq_{it} + \beta_5 lnSen_{it} + \beta_6 PubSocSp_{it} + Control_{it}\beta_7 + \varepsilon_{it}$$

[15] In this paper, we do not control for educational endowment proxied by an index of human capital per person (source: PWT) and for urban population (percentage of total) (source: WB), because both variables are highly correlated with economic development.

where $lnDis_{it}$ is the *ln* of natural or technological disaster outcomes (i.e. human or economic) for country *i* at time $t$, $lnGDPpc_{it}$ is the *ln* of GDP per capita for country *i* at time $t$, $\ln\left(\frac{GDPpc_{it}}{GDPpc_{it-1}}\right)$ is the *ln* of the annual growth rate for country *i* at time $t$, $\ln\left(\frac{GDPpc_{it}}{GDPpc_{it-5}}\right)$ is the *ln* of the 5-year growth rate for country *i* at time $t$, $IncIneq_{it}$ is the Gini index of net- or market-income inequality for country *i* at time $t$, $lnSen_{it}$ is the *ln* of Sen's social welfare index (net- or market-social welfare) for country *i* at time $t$, $PubSocSp_{it}$ is the public social spending for country *i* at time $t$, $Control_{it}$ is a vector of national control variables (i.e. *ln* of number of disasters, *ln* of employment, tfp, *ln* of population density, and population in the largest city), and $\varepsilon_{it}$ is the error term. $\beta_0$ is the constant, $\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$, $\beta_5$ and $\beta_6$ are coefficients or elasticity coefficients, and $\beta_7$ is a vector of coefficients and/or elasticity coefficients for the control variables.

We then use the following econometric specification to examine the impact of disaster outcomes on the short-term and long-term economic growth:

$$\ln\left(\frac{GDPpc_{it+1}}{GDPpc_{it}}\right) = \gamma_0 + \gamma_1 lnHumDis_{it} + \gamma_2 lnEconDis_{it} + \gamma_3 Controls_{it} + \varepsilon_{it}$$

or

$$\ln\left(\frac{GDPpc_{it+5}}{GDPpc_{it}}\right) = \gamma_0 + \gamma_1 lnHumDis_{it} + \gamma_2 lnEconDis_{it} + \gamma_3 Controls_{it} + \varepsilon_{it}$$

where $\ln\left(\frac{GDPpc_{it+1}}{GDPpc_{it}}\right)$ and $\ln\left(\frac{GDPpc_{it+5}}{GDPpc_{it}}\right)$ are the annual economic growth (i.e. short-term growth) and the 5-year economic growth (i.e. long-term growth), respectively, for country *i* at time *t*, $lnHumDis_{it}$ is the *ln* of natural or technological human disaster for country *i* at time $t$, $lnEconDis_{it}$ is the *ln* of natural hazard-associated economic disaster for country *i* at time $t$, $Control_{it}$ is a vector of national control variables (i.e. *ln* of GDP per capita, net- or market-income inequality, *ln* of net- or market-social welfare, *ln* of number of disasters, *ln* of employment, tfp, *ln* of population density, and population in the largest city).

These econometric specifications include both spatial and temporal variation. The empirical analysis exploits the unbalanced panel structure of the dataset for 175 countries from 1960 to 2015 by both Ordinary Least Squares (OLS) and Fixed Effects (FE) estimation. In the OLS estimation, the error term is specified as $\varepsilon_{it} = u_t + \epsilon_{it}$, where $u_t$ is a vector of time-dummies which controls for all time-specific national-invariant variables (Baltagi 2005), such as climate change effects and technological improvements effects (Tselios and Tompkins 2017), as well as controlling for possible improvements in EM-DAT after 1988, and $\epsilon_{it}$ is the disturbance term. The OLS coefficients reflect long-run effects because they allow for both inter-country (across-country) and intra-country (within-country) variation from the data (Durlauf and Quah 1999; Mairesse 1990; Partridge 2005; Griliches and Mairesse 1984).[16] In the FE estimation, the error term is specified as $\varepsilon_{it} = u_t + \omega_i + \epsilon_{it}$, where $\omega_i$ is the unobservable time-invariant national specific effects. The FE estimator controls for the effects of the omitted variables that are peculiar to each nation and therefore accommodates national heterogeneity. In other words, the FE model holds constant (fixes) the average effects of each country. The time-invariant national specific effects may include the effects of topography, mountains, the physical geography of coasts and natural resources, which are usually time-invariant characteristics, and may affect exposure to hazards (Tselios and Tompkins 2017). The FE estimator wipes out all the national-specific time-invariant variables, reducing the risk of obtaining biased estimation results, but this reduction in bias comes at a significant cost, as it removes cross-national (inter-country) variation from the data, potentially affecting the efficiency of the parameter estimates (Baltagi 2005; Higgins and Williamson 1999; Rodríguez-Pose and Tselios 2010). By including fixed effects, we control for the differences across countries in any observable or unobservable predictors. The FE coefficients reflect short/medium-run effects or time-series effects, because they soak up all cross-national differences (across-group variation) and what is left over is within-group variation (Durlauf and Quah 1999; Mairesse 1990; Partridge 2005; Griliches and Mairesse 1984). From a theoretical point of view, the distinction between the long-run and the short-run effect is very important, because part of the impact of natural and technological disasters depends on the country's ability to cope with the short-run and the long-run effects of a disaster and the resilience. Finally, the regression results are likely to suffer from some causation because national wealth, income inequality and social welfare are both a cause and consequence of disaster risk (Wisner et al. 2004).



## 4. The drivers of disaster resilience: regression results

Our analysis recognizes the complexity of the relationship between disasters and development, and hence the analysis considers both (a) the influence of national wealth, income inequality and social welfare on disaster outcomes and (b) the human and economic impact of disasters on economic growth. Both of these aspects are discussed in relation to natural and then to technological hazards.

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[16] The inter-country variation is the variation in the average quantity from one country to the next, while the intra-country variation is the variation within each country over time.

***4.1 Disaster outcomes from natural hazards***

*4.1.1 The influence of national wealth, income inequality and social welfare on natural disaster outcomes*

Table 2 presents the influence of national wealth (i.e. economic output, annual growth and 5-year growth), income inequality (i.e. the Gini index of net-income inequality and the Gini index of market-income inequality) and social welfare (i.e. Sen's index and public social spending) on natural hazard-associated disaster outcomes in terms of human impact and economic impact, after controlling for the number of disasters, the employment level, the tfp, the population density, the population in the largest city and the time-specific national-invariant variables (i.e. time-dummies). Regressions 1-8 have been estimated by OLS and Regressions 9-16 by FE (i.e. controlling for time-invariant national-specific effects). In all regressions, the variance inflation factors (VIFs) have been used to test for multicollinearity. The VIFs do not exceed the 'rule of thumb' value of 10, implying that the variance of the estimated regression coefficients is not affected by collinearity. The coefficients on national wealth and income inequality show the influence of national wealth and income inequality on disaster outcomes for almost all countries in the world for the period 1965-2014, while the coefficients on social welfare show the influence of social welfare for the OECD countries for the period 1990-2014.

The results show that natural disasters have a greater human impact on less economically developed countries (i.e. countries with relatively low GDP per capita, which is a proxy for national output and therefore national wealth) than on more developed ones (Regressions 1-2 and 9-10). The number of total people injured, made homeless, requiring immediate assistance and killed is higher for less economically developed countries than for more developed ones. However, natural disasters have a greater long-run economic impact on more economically developed countries (Regressions 5-6), possibly because more extensive infrastructure can be found in these countries which is costly to mend if damage occurs. Overall, there is evidence that '*high-income countries suffer from huge economic losses in disasters, but people in low-income countries pay with their lives*' as U.N. chief Ban Ki-moon said in a message for the annual International Day for Disaster Reduction (UNISDR 2016).

As for economic growth, there is no robust evidence that annual growth and 5-year growth affect natural disaster outcomes in terms of human and economic effects in the long-run (OLS estimator). Nevertheless, there is some evidence for a negative association in the short-run (FE estimator) (a) between 5-year growth and human impact (Regressions 9-10), and (b) between annual growth and economic impact (Regressions 13-14). Therefore, countries with faster growing GDP per capita tend to experience lower levels of human and economic loss from natural disasters in the short-run (Tselios and Tompkins 2017), but this effect disappears in the long-run.

Income inequality matters for natural disaster outcomes. The results show that an increase in net-income inequality increases the human impacts of natural disasters (Regression 1), and an increase in market-income inequality increases both the human and economic impacts from natural disasters but after controlling for fixed effects (Regressions 10 and 14). The positive relationship between income inequality and natural disasters is likely to denote the fact that poor households are more vulnerable to natural shocks in both the response phase (which is usually a short-run phase) and the recovery phase (which is usually a long-run phase) and countries which are more exposed to natural disasters may also experience higher inequality than those that are less affected.

The net- and market-Sen's index is negatively associated with human impacts of natural disasters for the OECD countries regardless of the estimator (Regressions 3, 4, 11 and 12), and public social spending is negatively associated with human impacts but only after controlling for fixed effects (Regressions 3 and 4). Therefore, the higher the social welfare, the lower the human impacts. We can hypothesise about the causes of this, for example, this could be because countries with strong welfare states contribute to people living in safer conditions and play a better role in both the preparation for and response to disaster events than countries with weak welfare states. In the former countries, mitigating actions may be taken to reduce human disaster outcomes, while in the latter countries the lack of social protection could mean that people are forced to use their assets to buffer disaster losses. Greater social welfare is expected to lead to more appropriate and sustainable human disaster risk reduction interventions. Therefore, the findings make the case for social protection being an important tool for managing the human risk of natural hazards. Nevertheless, the results do not show evidence of any relationship between social welfare and the economic impacts of natural disasters (Regressions 7, 8, 15 and 16).

We then examine whether the influence of national wealth and income inequality on natural hazard-associated disasters is stronger or weaker for poor countries than for other countries (Appendix 1)[17]. Here, we define poor countries as countries with GDP per capita below the 10$^{th}$ percentile of GDP per capita of the countries in the merged dataset. We observe that there are no differences in the effect of national wealth (both economic development and economic growth), but there are some



[17] We do not examine whether the influence of social welfare on natural hazard-associated disasters is stronger or weaker for poor countries than for other countries, because data on social welfare (i.e. public social spending) are available only for OECD countries.

differences in the effect of income inequality in the short-run. More specifically, the detrimental effect of net- and market-income inequality on human outcomes from natural disasters is more relevant for poor countries than for other countries after controlling for fixed-effects (Appendix 4). This may denote the fact that the relatively poorest and least powerful people already live in a situation with poor water supply and sanitation, and lack of infrastructure, which is compounded by natural disasters (Ferrier and Spickett 2007).

As for the control variables, the results in Table 2 show that there is a positive association between the number of natural disasters and the human and economic natural disaster outcomes (Regressions 1-16). Moreover, an increase in the employment level implies an increase in disaster outcomes (Regressions 1-8), but this effect disappears after controlling for fixed effects (Regression 9-16). The effects of the other controls, i.e. tfp, population density and population in the largest city, are sensitive to the empirical specification.

*4.1.2 The human and economic impact of natural disasters on economic growth*

Table 3 displays the human and economic impact of natural hazard-associated disasters on annual and 5-year economic growth after controlling for GDP per capita, income inequality, social welfare, the number of disasters, the employment level, the tfp, the population density, the population in the largest city and the time-specific national-invariant variables. Regressions 1-8 have been estimated by OLS and Regressions 9-16 by FE. Once more, in all regressions, the VIFs have been used to test for multicollinearity. Appendix 5 displays the differences in the human and economic impact on economic growth between poor and other countries.

The results do not show evidence that the human impacts of natural hazard-associated disasters delay economic growth for all countries in the world (Regressions 1-16), but this is relevant only for poor countries (Appendix 5). One of the reasons behind the robust negative association between human impacts and economic growth for poor countries is that natural disasters have serious welfare consequences for affected populations and local labour markets undermine economic growth. Poor countries do not have the necessary resources to cope with and recover from natural disasters (Jones et al. 2011; Noy 2009). In poor countries, natural disasters trap people in a cycle of poverty, because their buildings are poorly constructed and they have limited resources for disaster response and rebuilding.

The economic impacts of natural disasters seem to delay the long-term economic growth (i.e. 5-year growth) (Regressions 5-6 and 13-14), but especially for non-poor countries (Appendix 5). Thus, there seems to be evidence that the negative economic impacts of disasters on long-term growth are higher in rich countries than in poor ones, possibly because the physical capital investments are higher in rich countries. Moreover, there is no evidence that natural disasters may provide the impetus to update the capital stock and adopt new technologies, leading to increases in economic growth in the long-run (Skidmore and Toya 2002; Caballero and Hammour 1994). In poor countries, the higher economic cost of natural disasters is correlated with higher short-term growth. According to the traditional neoclassical growth models, the destruction of capital stock in poor countries due to natural disasters may boost short-run growth, possibly because it moves countries away from their steady-state levels of macroeconomic objectives (Shabnam 2014).

The control variables are discussed very briefly. We observe that there is evidence of convergence in GDP per capita in the long-run (Regressions 5-6 and 13-14) and there is a negative association between public social spending and economic growth (Regressions 3-4, 7-8, 11-12 and 15-16). The results of the other control variables are sensitive to the empirical specification.

***4.2 Disaster outcomes from technological hazards***

*4.2.1 The influence of national wealth, income inequality and social welfare on technological disaster outcomes*

Table 4 displays the regression results for technological disaster outcomes (i.e. human impact). First of all, there is neither evidence that national wealth (i.e. economic output, annual growth and 5-year growth) matters for human impact of technological disasters (Regressions 1-8) nor evidence for differences between poor and other countries (Appendix 6). The results show that an increase in net-income inequality in OECD countries is associated with a long-run decrease in human impact (Regression 3). The negative relationship between net-income inequality and technological disasters is likely to highlight the fact that all households in OECD countries are vulnerable to technological shocks, especially in the recovery phase (because the response phase is usually a short-term phase), and OECD countries which are more exposed to technological disasters may experience lower income inequality than those that are less affected. The results also show that the higher the public social spending, the lower the short-run human impacts from technological disasters (Regressions 7-8). Countries with a strong social protection system reduce the risk for the human effects of technological disasters. Therefore, there is evidence that mitigating actions are key tools for human disaster risk reduction. As for the control variables, an increase in the number of disasters is associated with an increase in human impacts. The employment level positively affects human impacts, but only in the long-run. Finally, the higher the population in the largest city of a country, the higher the human impacts, which means that metropolitan areas (especially those of non-OECD countries) are more exposed to technological disasters than other areas.

*4.2.2 The human impact from technological disasters on economic growth*

Table 5 presents the human impact of technological disaster on economic growth. Human impact does not seem to matter for annual and 5-year economic growth either with or without time-invariant national-specific effects. However, there is a very strong evidence that an increase in the human impact of technological disasters in poor countries is associated with a reduction in both the annual and the 5-year growth (Appendix 7). Similar to natural disasters, technological disasters may have serious welfare consequences for the affected populations and local labour markets undermining economic growth. Poor countries may not have the necessary resources to cope with and recover not only from natural disasters but also from technological disasters. People in poor countries may be stressed, especially because technological disasters are usually unpredictable, and may feel collectively frustrated with public officials and with those who manage the technology (Gill and Picou 1998; Weisaeth, Knudsen, and Tonnessen 2002). The coefficients on the control variables are sensitive to the empirical specifications.



## 5. Conclusions

This paper aims to advance understanding of the influence of national wealth, income inequality and social welfare on disaster outcomes in terms of human effects (i.e. the number of people injured, people made homeless, people requiring immediate assistance, and people killed) and economic effects (i.e. the estimated damage to property, crops and livestock), as well as the impact of these outcomes on economic growth. Our analysis enables us to draw out some concrete conclusions.

For natural disasters, we conclude that there is a greater human impact but a lower economic impact on less economically developed countries than on more developed ones. Another way of looking at this is that developed countries suffer huge economic losses in natural disasters, but people in developing countries pay with their lives. This may be because high-wealth countries have more risk mitigation measures in place to reduce the extent of damage and more social policies and actions in place to reduce the human impact of the next disaster than the less-wealthy and more unequal ones (World Bank and United Nations 2010).

Our findings also indicate that an increase in income inequality is associated with an increase in the human impacts of natural disasters. This finding reinforces earlier work which shows a positive relationship between income inequality and disasters. Case-study research suggests that this could be because poor households are more vulnerable to natural shocks in both the response and the recovery phase. Our findings also support the location-specific work of Bui et al. (2014) and Fothergill and Peek (2004), who note that countries which are more exposed to disasters may also experience higher inequality than those less affected. This could be due to the multiple vulnerabilities that inequality can create, for example, excluded or marginalized people often live in unsafe urban areas; their housing is poorly built and can be easily damaged; unequal countries may not invest in early warning systems to provide universal benefits, and weak social safety network may limit capacity to cope with disasters (Zorn 2018). Natural disasters have the potential to cause social unrest in places of high inequality, which can lead to additional economic and human losses (Yamamura 2015). Our findings highlight that this is not an issue unique to one country, but is a trend that can be seen across many countries with high inequality, thus reinforcing the need to address income inequality as an important priority element of disaster risk reduction.

Our research provides evidence that social welfare (i.e. both Sen's indexes and public social spending) in OECD countries is negatively associated with human impacts. In other words, it appears that OECD countries, which invest in social welfare mitigating actions, experience reduced human disaster outcomes. Our findings reinforce theoretical and case-based assessments in the literature which show that local scale social service provision can contribute to disaster resilience (Rapeli et al. 2018). There is also evidence that safety net assistance and insurance can reduce disaster risk, improve welfare (Teh 2017), and social allowances can help households strengthen their resilience to disasters (Arouri, Nguyen, and Ben Youssef 2015). Generally, for the developed world, social protection is considered an important tool for managing the human risk of hazards, e.g. social safety nets and other components of social protection are likely to prevent and mitigate the impact of natural disasters in terms of human impacts (Sann et al. 2012). However, we find no conclusive evidence that in the developing world, countries with high provision of social welfare recover more quickly from disasters than countries with low provision. This is not a recommendation to remove social welfare programming, but offers an insight into the more important underlying drivers of vulnerability, i.e. income inequality should be a higher priority to address disaster risk than provision of social welfare.

As for the impact of natural disaster effects on economic growth, the results show that the human impacts of disasters delay the economic growth of poor countries. This is not a new finding, however, we are able to show that this is a conclusive long-term trend for all developing countries. Natural disasters do not provide long-term development opportunities as aid flows in, but as with low income communities trapped in cycles of poverty, low income countries which are highly exposed to hazards can become trapped in disaster-driven development doldrums, unable to escape.

As far as the technological disasters are concerned, there is no evidence that national wealth and income inequality are associated with human effects for all countries in the world. However, there is some evidence that an increase in public social spending in OECD countries is related to a decrease in the human impacts of disasters. A possible conclusion from this is that risk mitigation of OECD countries are key tools for human disaster risk reduction. Finally, an increase in the human impacts of technological disasters for poor countries undermines economic growth. Other results show that the largest cities of non-OECD countries are more exposed to technological disasters than other cities.

Our findings add insight into the understanding of the impacts of disasters on development and growth: poor countries which are frequently and badly affected by natural disasters are less likely to be able to maintain rates of economic growth. Under a changing climate, as Hallegatte, Hourcade, and Dumas (2007) point out, this could mean that the costs of adapting to extreme events in the developing world could be much higher than currently anticipated, and that the impacts of climate change could undermine economic development potential.

Where does this paper leave us in terms of progress towards Sendai and the SDGs? Our findings reinforce the importance of taking into account the drivers of vulnerability in understanding disaster outcomes, to identify the groups in society already under pressure and most at risk before a disaster happens. But, what is needed specifically? Our findings point to the importance of addressing income inequality to reduce pre-disaster vulnerability, as a priority over provision of social welfare to address post disaster impacts. This matters for both policy and research. Resources for development, climate change adaptation and disaster risk that focus on post-disaster support (e.g. social welfare) may become increasingly insufficient to address low income countries' needs. Therefore, policy focus needs to be drawn to the front of the disaster risk reduction cycle (i.e. address inequality), and away from the focus on recovery. Funds need to be spent on addressing social and economic inequality, through policy that supports universal access to land, access to power, access to assets and access to opportunity. Such an approach would work hand-in-hand with the focus of the SDGs, i.e. (4) Quality Education; (5) Gender Equality; (6) Clean Water and Sanitation;

(7) Affordable and Clean Energy; (8) Decent Work and Economic Growth; (9) Industry, Innovation and Infrastructure; (10) Reduced Inequality; (11) Sustainable Cities and Communities; and (16) Peace and Justice Strong Institutions.

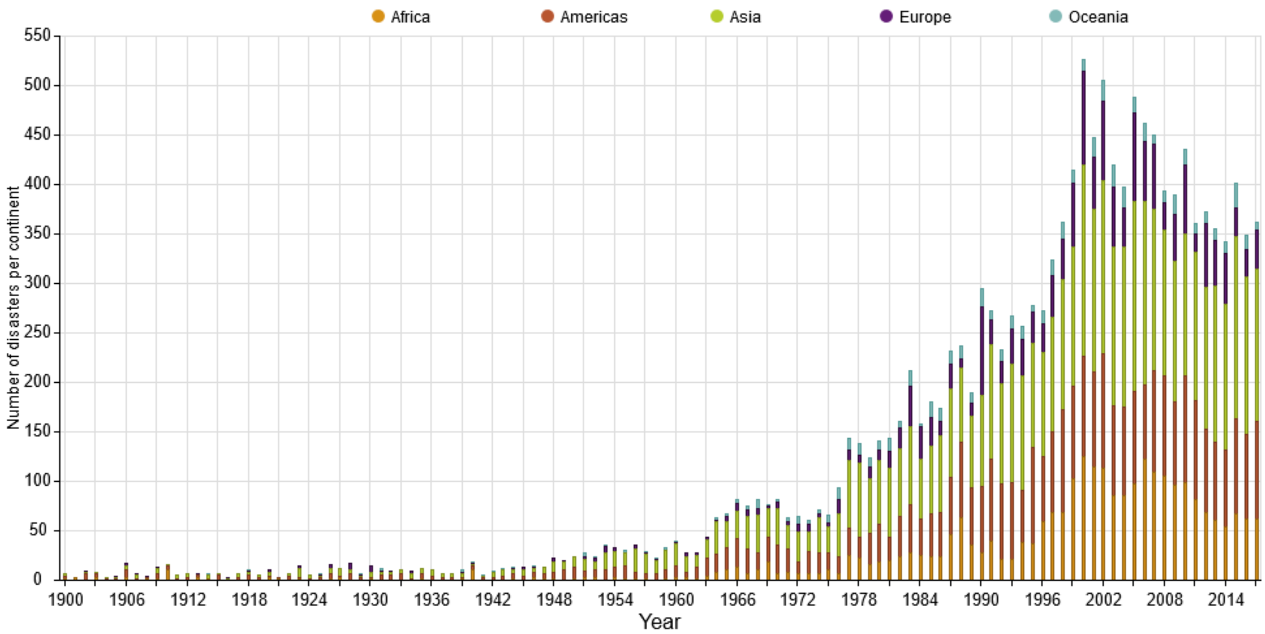
Despite these findings and policy recommendations, many questions remain open to be analysed in greater depth. This paper examined the 'whether', i.e. whether higher national wealth, lower income inequality and higher social welfare provisioning can reduce the human and economic impacts of natural and technological disasters and whether these disasters can affect economic growth, but it did not examine the mechanisms of these associations, i.e. the 'how'. In terms of research priorities, we reinforce the need for more global scale analyses of trends in drivers of disaster risk and disaster vulnerabilities, to draw out global priorities on disaster risk reduction. In addition, we recommend more detailed global analyses of the dimensions of inequality that have the most damaging impacts on disaster outcomes. Research of this nature could help clarify where policy to address inequality should focus, and would enable a more careful targeting of resources to achieve the Sendai obligations and the SDGs.

**Acknowledgement**

We would like to thank the three anonymous reviewers for their very helpful comments which significantly improved this paper.

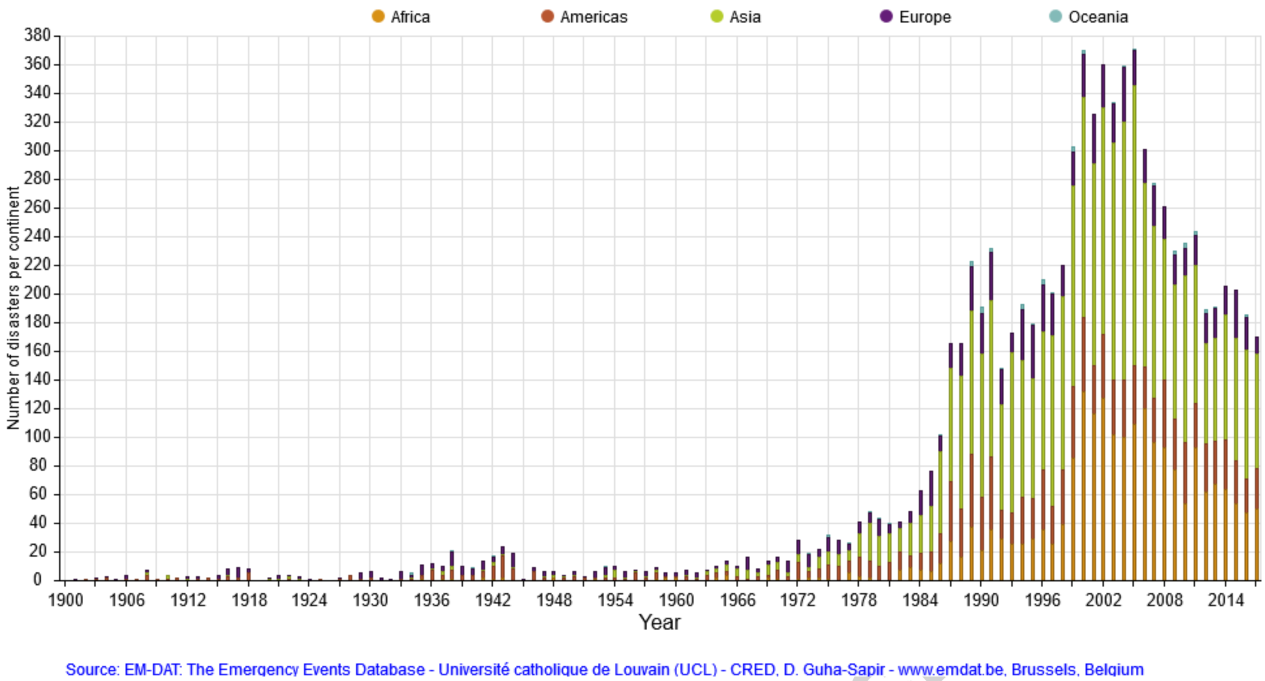
**Appendix 1: Total number of reported natural and technological disasters between 1900 and 2017**

a) Natural disasters



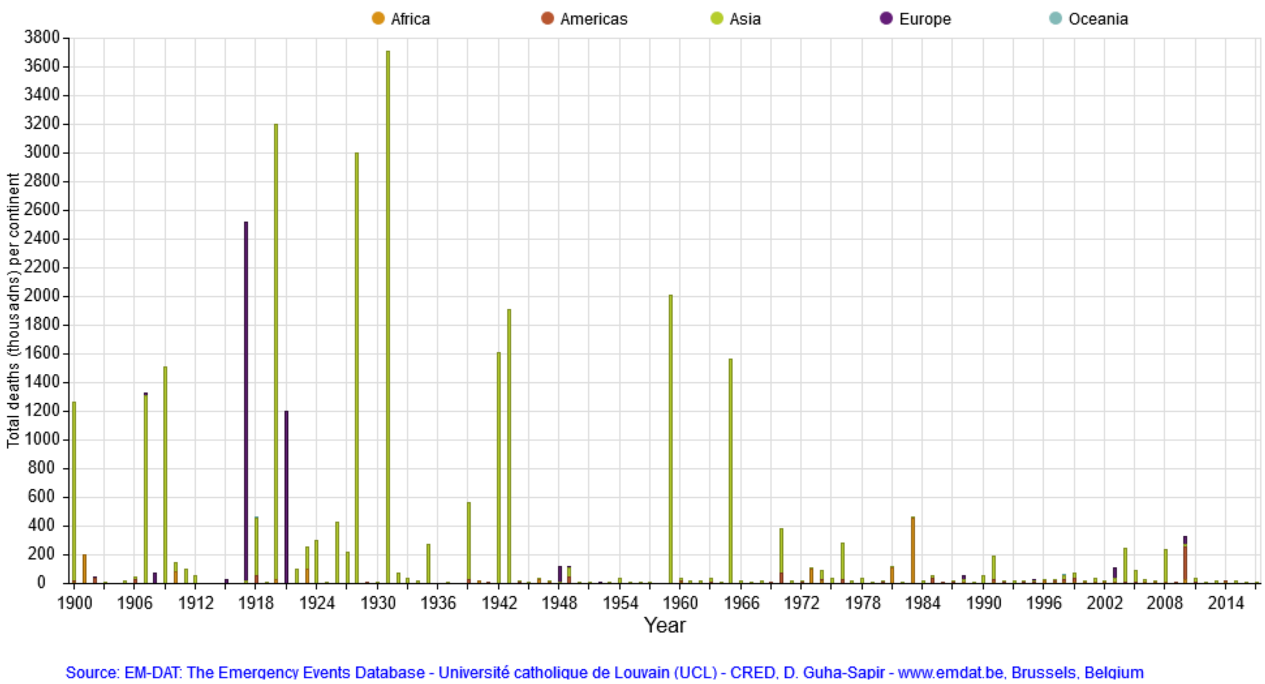

Source: EM-DAT: The Emergency Events Database - Université catholique de Louvain (UCL) - CRED, D. Guha-Sapir - www.emdat.be, Brussels, Belgium

b) Technological disasters

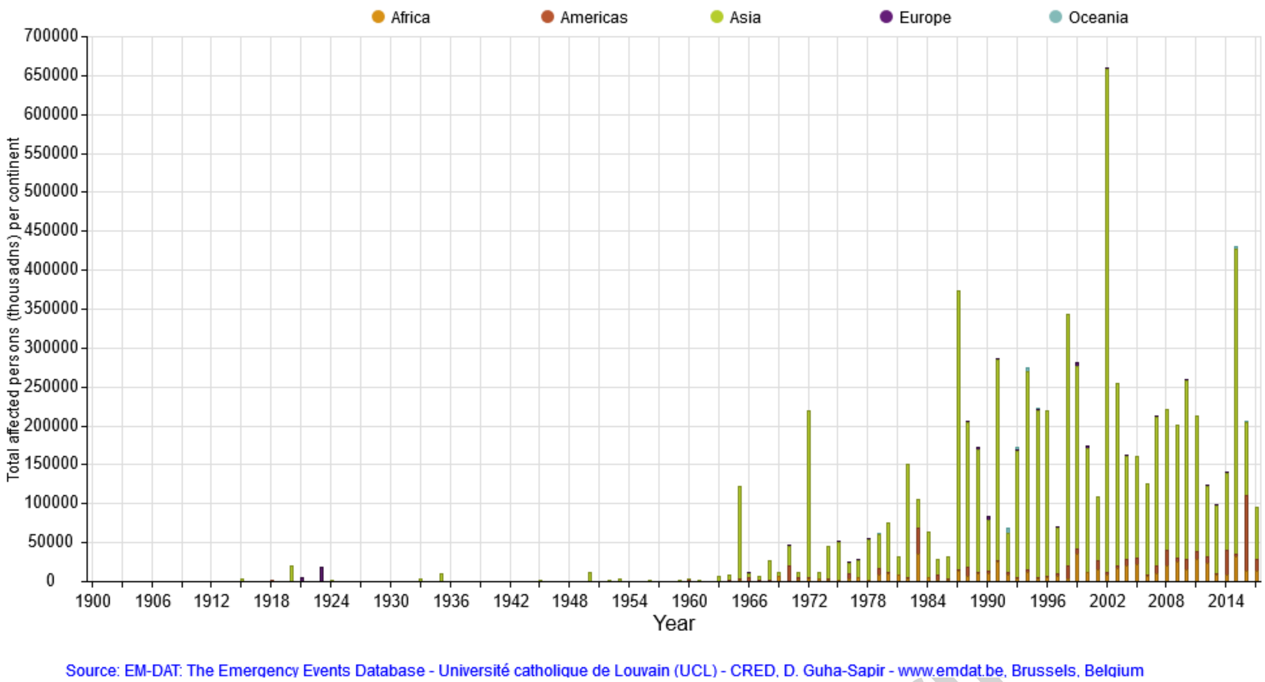



**Appendix 2: Total deaths, total affected persons and total damage caused by reported natural and technological disasters**

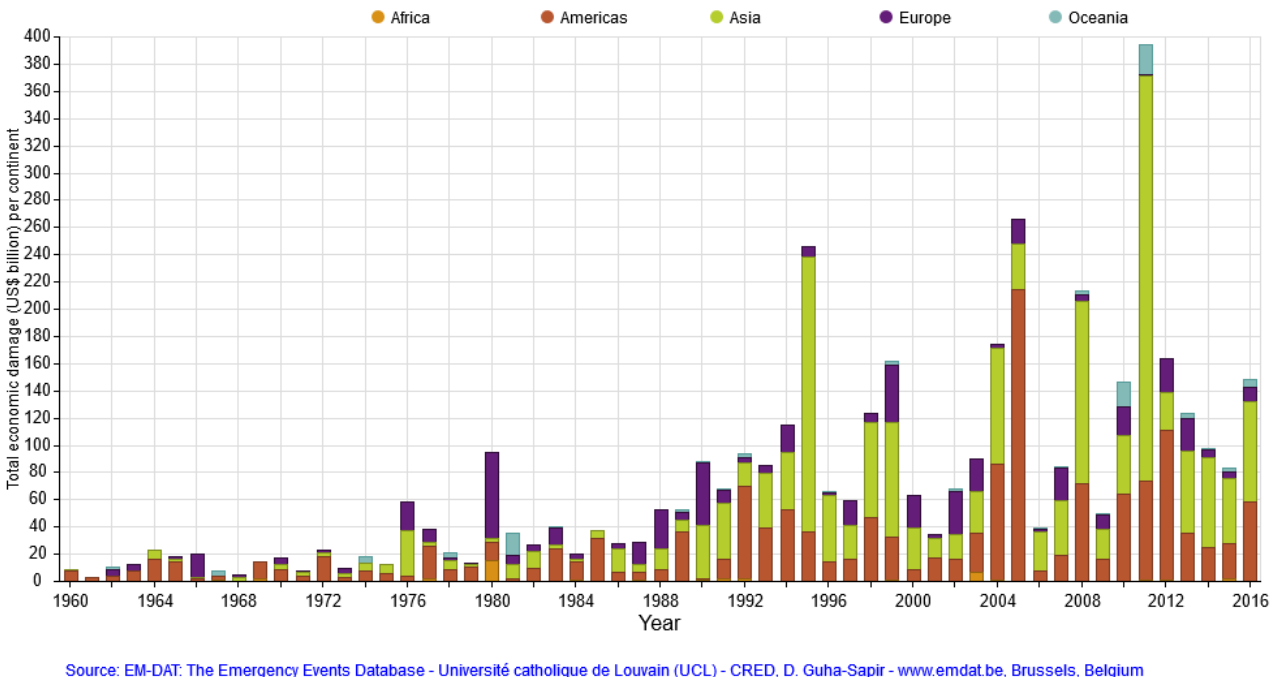
a) Natural disasters: total deaths per continent between 1900 and 2017




b) Natural disasters: total affected persons per continent between 1900 and 2017

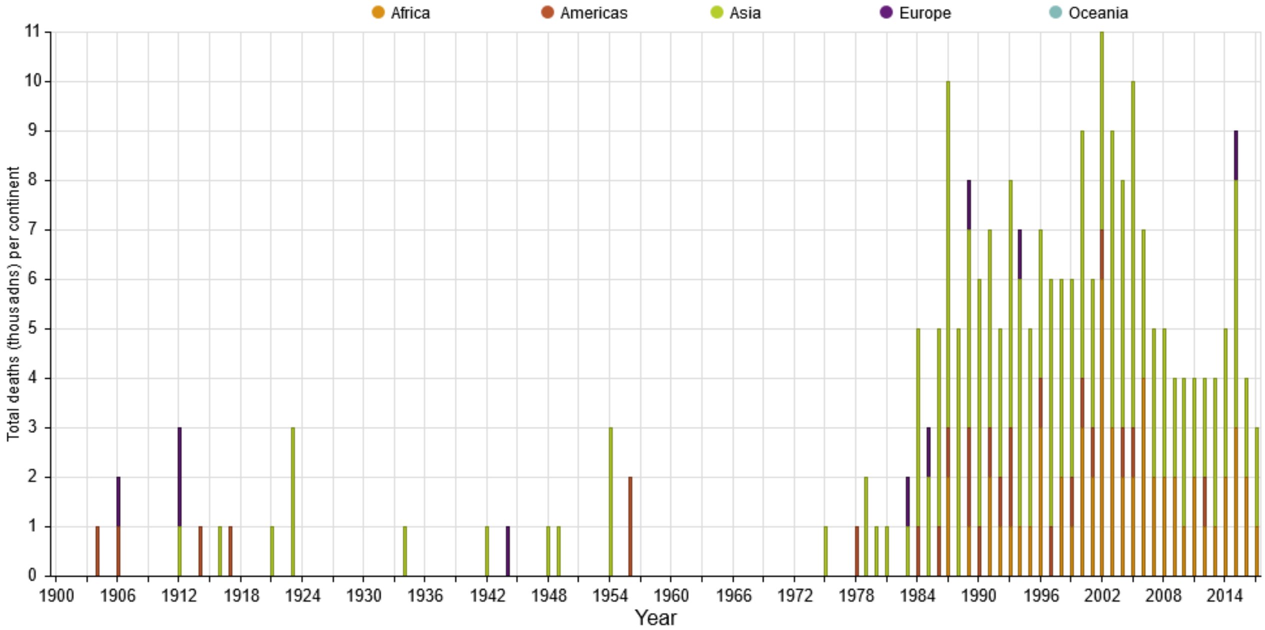



c) Natural disasters: total damage per continent between 1960 and 2016



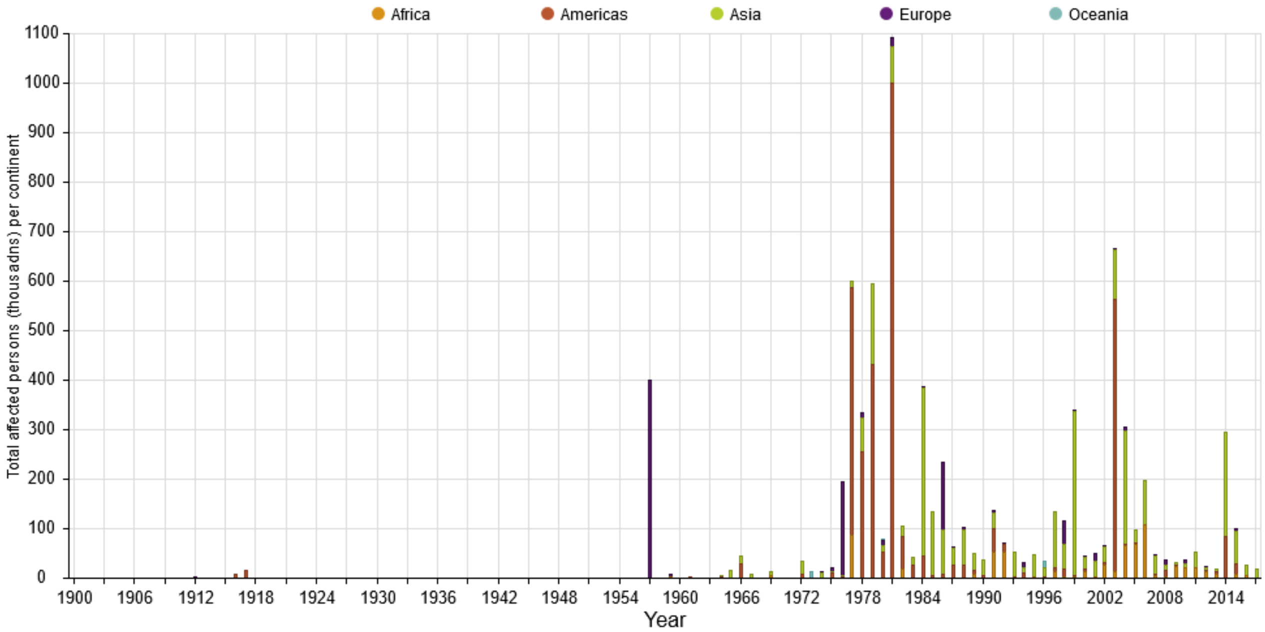

Note: Values for the indicator Total damage (Values scaled to 2016 US$) ARE NOT available for years before 1960

d) Technological disasters: total deaths per continent between 1900 and 2017



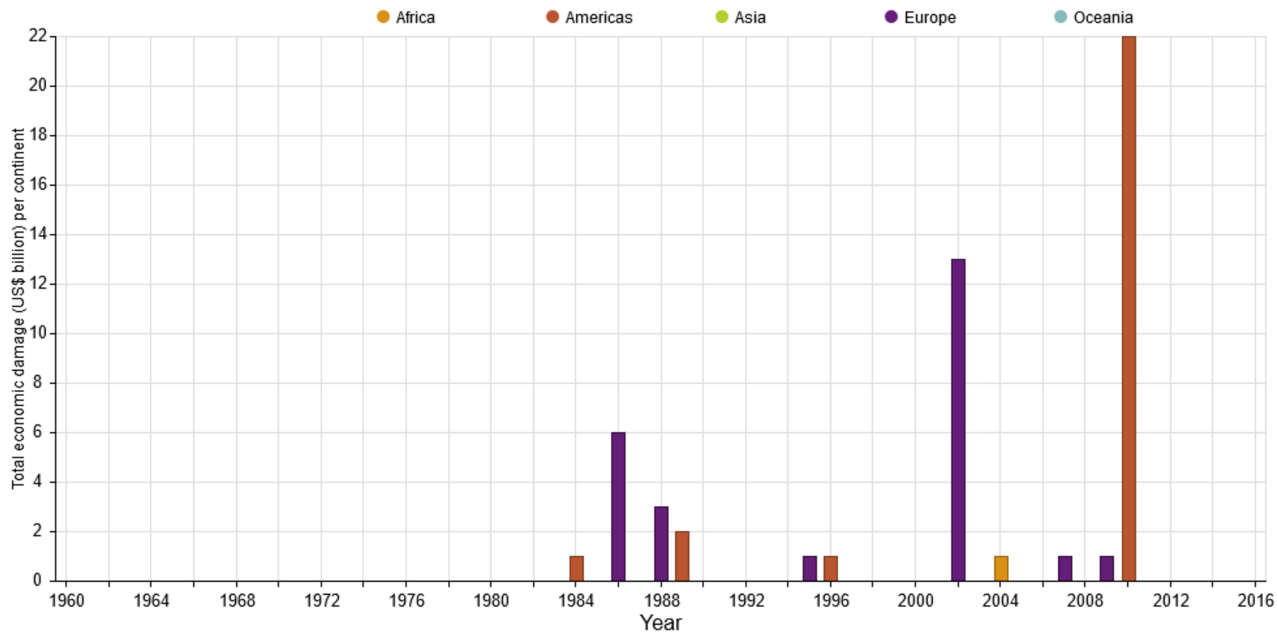

Source: EM-DAT: The Emergency Events Database - Université catholique de Louvain (UCL) - CRED, D. Guha-Sapir - www.emdat.be, Brussels, Belgium

e) Technological disasters: total affected persons per continent between 1900 and 2017




Source: EM-DAT: The Emergency Events Database - Université catholique de Louvain (UCL) - CRED, D. Guha-Sapir - www.emdat.be, Brussels, Belgium

f) Technological disasters: total damage per continent between 1960 and 2016




Source: EM-DAT: The Emergency Events Database - Université catholique de Louvain (UCL) - CRED, D. Guha-Sapir - www.emdat.be, Brussels, Belgium

Note: Values for the indicator Total damage (Values scaled to 2016 US$) ARE NOT available for years before 1960



**Appendix 3: Correlation matrix**

| | GDP per capita (ln) | Annual growth (ln) | 5-year growth (ln) | Net-income ineq | Market-income ineq | Net-Sen's index (ln) | Market-Sen's index (ln) | Public social spending | Number of natural disasters (ln) | Number of technological disasters (ln) | Employment (ln) | tfp | Population density (ln) | Pop in the largest city |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| GDP per capita (ln) | 1 | | | | | | | | | | | | | |
| Annual growth (ln) | 0.0378 | 1 | | | | | | | | | | | | |
| 5-year growth (ln) | 0.0894 | 0.5165 | 1 | | | | | | | | | | | |
| Net-income ineq | -0.4431 | 0.0103 | -0.0804 | 1 | | | | | | | | | | |
| Market-income ineq | -0.1349 | -0.0469 | -0.1872 | 0.7839 | 1 | | | | | | | | | |
| Net-Sen's index (ln) | 0.9931 | 0.0343 | 0.0938 | -0.5448 | -0.2272 | 1 | | | | | | | | |
| Market-Sen's index (ln) | 0.9913 | 0.0423 | 0.1087 | -0.5321 | -0.2627 | 0.997 | 1 | | | | | | | |
| Public | 0.4 | - | - | - | 0.1 | 0.5 | 0.4 | 1 | | | | | | |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| social spending | 844 | 0.2795 | 0.3498 | 0.5977 | 947 | 504 | 302 | | | | | | | |
| Number of natural disasters (ln) | 0.0069 | 0.0441 | 0.0506 | 0.088 | -0.0103 | -0.0023 | 0.0099 | -0.2265 | 1 | | | | | |
| Number of technological disasters (ln) | -0.1114 | 0.0472 | 0.1267 | 0.2235 | 0.0615 | -0.1319 | -0.1165 | -0.3114 | | 1 | | | | |
| Employment (ln) | 0.0073 | 0.0312 | 0.0652 | -0.055 | -0.1338 | 0.0157 | 0.0261 | -0.1009 | 0.6132 | 0.6224 | 1 | | | |
| tfp | 0.179 | 0.0326 | 0.093 | 0.1892 | 0.2155 | 0.1393 | 0.1441 | 0.0772 | -0.0582 | -0.1038 | -0.0865 | 1 | | |
| Population density (ln) | 0.0435 | 0.0636 | 0.1394 | -0.0959 | -0.1097 | 0.0563 | 0.0631 | 0.0843 | 0.0881 | 0.1012 | 0.1103 | -0.1303 | 1 | |
| Pop in the largest city | -0.1667 | 0.0251 | 0.034 | 0.2874 | 0.148 | -0.1931 | -0.1808 | -0.3097 | -0.3083 | -0.3425 | -0.5886 | 0.0272 | 0.2073 | 1 |

**Appendix 4: The influence of national wealth and income inequality on natural disaster outcomes for poor countries**

| | OLS Human impact (ln) (1) | OLS Human impact (ln) (2) | OLS Economic impact (ln) (3) | OLS Economic impact (ln) (4) | FE Human impact (ln) (5) | FE Human impact (ln) (6) | FE Economic impact (ln) (7) | FE Economic impact (ln) (8) |
|---|---|---|---|---|---|---|---|---|
| GDP per capita (ln) | | | | | | | | |
| • Poor countries | -1.2802*** | -1.7915*** | 1.2503 | 1.0418* | -1.5529* | -1.4838* | -1.5276 | -1.6143 |
| • Other countries | -1.3841*** | -1.7737*** | 0.5162*** | 0.5876*** | -1.3114* | -1.3329* | -0.4212 | -0.5418 |
| Annual growth (ln) | | | | | | | | |
| • Poor countries | -3.4457 | -3.1992 | -12.2827 | -14.5849 | -3.9480 | -3.7775 | -11.4215 | -11.6656 |
| • Other countries | -1.1628 | -1.3898 | -2.5297 | -2.4575 | -1.9761 | -2.0831 | -5.4170* | -5.8660** |
| 5-year growth (ln) | | | | | | | | |
| • Poor countries | 2.5044* | 2.3282 | -1.1547 | 0.5634 | 0.3528 | 0.3026 | 9.3826 | 9.9347 |
| • Other countries | 0.2929 | 0.1456 | -0.2282 | -0.1294 | -1.2735** | -1.2647** | -0.2912 | -0.3675 |
| Net-income | | | | | | | | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| ineq | | | | | | | | |
| • Poor countries | 0.0095 | | -0.1197 | | 0.1154* | | 0.1884 | |
| • Other countries | 0.0823*** | | -0.0076 | | 0.0404 | | 0.0297 | |
| Market-income ineq | | | | | | | | |
| • Poor countries | | -0.0418 | | -0.0493 | | 0.1153** | | 0.2143 |
| • Other countries | | 0.0180 | | 0.0122 | | 0.0590** | | 0.0633** |
| Number of disasters (ln) | 1.8661*** | 1.9390*** | 1.0840*** | 1.0782*** | 1.8545*** | 1.8487*** | 0.9964*** | 0.9941*** |
| Employment (ln) | 0.6143*** | 0.7322*** | 0.3939*** | 0.3822*** | 1.4721 | 1.7755 | 0.9899 | 1.4248 |
| tfp | -1.1911** | -0.1939 | -0.9041 | -1.2284* | 2.7268** | 2.8730** | 2.1476 | 2.4749 |
| Population density (ln) | -0.1512*** | -0.2513*** | 0.0367 | 0.0568 | 1.6956 | 2.0510 | -1.1039 | -0.6228 |
| Pop in the largest city | 0.0133** | 0.0294*** | -0.0098 | -0.0118* | 0.0416 | 0.0444 | -0.0559 | -0.0583 |
| Time-dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Fixed effects | NO | NO | NO | NO | YES | YES | YES | YES |
| Constant | 19.1762*** | 23.9668*** | 8.1110*** | 6.7339*** | 6.9768 | 4.1431 | 16.8617 | 13.4129 |
| Observations | 1,586 | 1,586 | 988 | 988 | 1,586 | 1,586 | 988 | 988 |
| R-squared | 0.5331 | 0.5168 | 0.3625 | 0.3626 | 0.2217 | 0.2238 | 0.1462 | 0.1505 |

*** p<0.01, ** p<0.05, * p<0.1

**Appendix 5: The human and economic impact of natural disasters on economic growth for poor countries**

| | OLS Annual growth (ln) (1) | OLS Annual growth (ln) (2) | OLS 5-year growth (ln) (3) | OLS 5-year growth (ln) (4) | FE Annual growth (ln) (5) | FE Annual growth (ln) (6) | FE 5-year growth (ln) (7) | FE 5-year growth (ln) (8) |
|---|---|---|---|---|---|---|---|---|
| Human impact (ln) | | | | | | | | |
| • Poor countries | -0.0092*** | -0.0093*** | -0.0306*** | -0.0304*** | -0.0106*** | -0.0106*** | -0.0237*** | -0.0243*** |
| • Other countries | 0.0004 | 0.0004 | 0.0023 | 0.0021 | 0.0009 | 0.0008 | 0.0030** | 0.0029** |
| Economic impact (ln) | | | | | | | | |
| • Poor countries | 0.0062* | 0.0063* | 0.0157 | 0.0158 | 0.0066* | 0.0065* | 0.0108 | 0.0108 |
| • Other countries | -0.0007 | -0.0007 | -0.0041* | -0.0038* | -0.0007 | -0.0008 | -0.0044** | -0.0045** |
| GDP per capita (ln) | -0.0078*** | -0.0071*** | -0.0353*** | -0.0315*** | -0.0934*** | -0.0905*** | -0.3790*** | -0.3652*** |
| Net-income ineq | -0.0001 | | -0.0010 | | 0.0022*** | | 0.0106*** | |
| Market-income ineq | | 0.0001 | | -0.0009 | | 0.0017*** | | 0.0059*** |
| Number of disasters (ln) | 0.0031 | 0.0031 | -0.0071 | -0.0073 | 0.0064** | 0.0068** | 0.0019 | 0.0028 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Employment (ln) | 0.0007 | 0.0006 | 0.0143** | 0.0129** | -0.0137 | -0.0166 | -0.1392** | -0.1616** |
| tfp | -0.0746*** | -0.0774*** | -0.3885*** | -0.3929*** | -0.0470** | -0.0454** | -0.2441*** | -0.2383*** |
| Population density (ln) | 0.0028** | 0.0030** | 0.0089** | 0.0096*** | -0.0551 | -0.0387 | 0.0589 | 0.1164 |
| Pop in the largest city | 0.0003* | 0.0003* | 0.0013*** | 0.0011** | -0.0002 | -0.0004 | -0.0007 | -0.0005 |
| Time-dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Fixed effects | NO | NO | NO | NO | YES | YES | YES | YES |
| Constant | 0.1647*** | 0.1531*** | 0.8010*** | 0.7780*** | 1.0593*** | 0.9954*** | 3.4301*** | 3.2791*** |
| Observations | 996 | 996 | 859 | 859 | 996 | 996 | 859 | 859 |
| R-squared | 0.2672 | 0.2671 | 0.4401 | 0.4400 | 0.3497 | 0.3475 | 0.5861 | 0.5702 |

*** p<0.01, ** p<0.05, * p<0.1

**Appendix 6: The influence of national wealth and income inequality on technological disaster outcomes for poor countries**

| | OLS Human impact (ln) (1) | OLS Human impact (ln) (2) | FE Human impact (ln) (3) | FE Human impact (ln) (4) |
|---|---|---|---|---|
| GDP per capita (ln) | | | | |
| • Poor countries | 0.0588 | 0.1323 | 0.4195 | 0.3860 |
| • Other countries | -0.0402 | -0.0073 | 0.3386 | 0.2070 |
| Annual growth (ln) | | | | |
| • Poor countries | -0.1397 | -0.1728 | -0.0745 | -0.0801 |
| • Other countries | -1.7339 | -1.7430 | -1.8693 | -1.9568 |
| 5-year growth (ln) | | | | |
| • Poor countries | -0.7970 | -0.8037 | -0.2367 | -0.3741 |
| • Other countries | 0.1525 | 0.2247 | 0.2157 | 0.2550 |
| Net-income ineq | | | | |
| • Poor countries | -0.0272 | | -0.0249 | |
| • Other countries | -0.0085 | | -0.0222 | |
| Market-income ineq | | | | |
| • Poor countries | | -0.0192 | | -0.0167 |
| • Other countries | | 0.0020 | | 0.0010 |
| Number of disasters (ln) | 1.2318*** | 1.2123*** | 1.3053*** | 1.3038*** |
| Employment (ln) | 0.1752*** | 0.1625*** | 0.1801 | 0.4446 |
| tfp | 0.8061** | 0.6925** | 0.5450 | 0.6448 |
| Population density (ln) | 0.0688** | 0.0814** | 0.5796 | 0.4712 |
| Pop in the largest city | 0.0106*** | 0.0085** | 0.0645** | 0.0606** |
| Time-dummies | YES | YES | YES | YES |
| Fixed effects | NO | NO | YES | YES |
| Constant | 4.2553*** | 3.5165** | -1.7375 | -1.6031 |
| Observations | 1,136 | 1,136 | 1,136 | 1,136 |
| R-squared | 0.5235 | 0.5227 | 0.3217 | 0.3207 |

*** p<0.01, ** p<0.05, * p<0.1

**Appendix 7: The human impact of technological disasters on economic growth for poor countries**

| | OLS Annual growth (ln) (1) | OLS Annual growth (ln) (2) | OLS 5-year growth (ln) (3) | OLS 5-year growth (ln) (4) | FE Annual growth (ln) (5) | FE Annual growth (ln) (6) | FE 5-year growth (ln) (7) | FE 5-year growth (ln) (8) |
|---|---|---|---|---|---|---|---|---|
| Human impact (ln) | | | | | | | | |
| • Poor countries | -0.0083*** | -0.0081*** | -0.0246*** | -0.0257*** | -0.0102*** | -0.0102*** | -0.0185*** | -0.0194*** |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| • Other countries | -0.0013 | -0.0013 | -0.0035 | -0.0036 | -0.0007 | -0.0007 | -0.0025 | -0.0031 |
| GDP per capita (ln) | -0.0042** | -0.0040** | -0.0096* | -0.0138*** | -0.0871*** | -0.0854*** | -0.3354*** | -0.3134*** |
| Net-income ineq | -0.0001 | | 0.0009 | | 0.0006 | | 0.0072*** | |
| Market-income ineq | | -0.0002 | | 0.0000 | | 0.0007 | | 0.0056*** |
| Number of disasters (ln) | 0.0010 | 0.0012 | 0.0087 | 0.0108 | 0.0044 | 0.0044 | 0.0279*** | 0.0290*** |
| Employment (ln) | 0.0036** | 0.0034** | 0.0058 | 0.0066 | -0.0314 | -0.0301 | -0.1689*** | -0.1758*** |
| tfp | -0.0528*** | -0.0515*** | -0.4117*** | -0.3996*** | 0.0109 | 0.0100 | -0.3324*** | -0.3480*** |
| Population density (ln) | 0.0020* | 0.0019* | 0.0108*** | 0.0094*** | 0.0240 | 0.0318 | 0.0113 | 0.0783 |
| Pop in the largest city | 0.0002 | 0.0002 | 0.0005 | 0.0007** | 0.0023*** | 0.0022*** | 0.0058*** | 0.0056** |
| Time-dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Fixed effects | NO | NO | NO | NO | YES | YES | YES | YES |
| Constant | 0.1368*** | 0.1419*** | 0.6525*** | 0.7124*** | 0.6968*** | 0.6493*** | 3.3783*** | 3.0154*** |
| Observations | 1,194 | 1,194 | 1,000 | 1,000 | 1,194 | 1,194 | 1,000 | 1,000 |
| R-squared | 0.2056 | 0.2063 | 0.3759 | 0.3742 | 0.2519 | 0.2527 | 0.5110 | 0.5085 |

*** p<0.01, ** p<0.05, * p<0.1

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**Table 1: Descriptive analysis**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Human impact (ln) of natural disasters | 2401 | 9.3601 | 3.8278 | 0.0000 | 19.6504 |
| Economic impact (ln) of natural disasters | 1294 | 12.3501 | 2.7552 | 2.1290 | 19.3728 |
| Human impact (ln) of technological disasters | 1652 | 5.0599 | 1.7631 | 1.6094 | 13.2184 |
| Economic impact (ln) of technological disasters | 116 | 10.6642 | 2.2849 | 3.9540 | 16.8441 |
| GDP per capita (ln) | 3765 | 9.0459 | 1.1283 | 6.0212 | 11.3435 |
| Annual growth (ln) | 3605 | 0.0261 | 0.0732 | -0.6202 | 0.8776 |
| 5-year growth (ln) | 3012 | 0.1279 | 0.1876 | -1.1848 | 1.2858 |

| | | | | | |
|---|---|---|---|---|---|
| Net-income ineq | 4082 | 36.5093 | 9.5945 | 14.0606 | 67.2118 |
| Market-income ineq | 4082 | 44.9038 | 8.3630 | 18.5258 | 76.8883 |
| Net-Sen's index (ln) | 3765 | 8.5702 | 1.2033 | 5.5841 | 11.0638 |
| Market-Sen's index (ln) | 3765 | 8.4265 | 1.1616 | 5.4722 | 10.7672 |
| Public social spending | 811 | 19.0408 | 6.0916 | 0.0000 | 34.1780 |
| Number of natural disasters (ln) | 2540 | 0.8589 | 0.8172 | 0.0000 | 3.7612 |
| Number of technological disasters (ln) | 1671 | 0.7816 | 0.8752 | 0.0000 | 4.2627 |
| Employment (ln) | 3746 | 1.5663 | 1.6651 | -5.2037 | 6.6759 |
| tfp | 3076 | 0.9332 | 0.1848 | 0.3042 | 4.3767 |
| Population density (ln) | 3872 | 4.1390 | 1.4483 | 0.3915 | 8.9407 |
| Pop in the largest city | 3551 | 30.8023 | 17.5931 | 2.6062 | 100.0000 |

**Table 2: The influence of national wealth, income inequality and social welfare on natural disaster outcomes**

*A. OLS estimator*

| | Human impact (ln)<br><br>(1) | Human impact (ln)<br><br>(2) | Human impact (ln)<br>OECD<br>(3) | Human impact (ln)<br>OECD<br>(4) | Economic impact (ln)<br><br>(5) | Economic impact (ln)<br><br>(6) | Economic impact (ln)<br>OECD<br>(7) | Economic impact (ln)<br>OECD<br>(8) |
|---|---|---|---|---|---|---|---|---|
| GDP per capita (ln) | -1.0174*** | -1.3714*** | | | 0.5159*** | 0.5839*** | | |
| Annual growth (ln) | -0.7575 | -0.6765 | -8.1053 | -7.2200 | -2.8560 | -2.7987 | -6.6902 | -7.3916 |
| 5-year growth (ln) | 0.9014* | 0.7766 | -1.5921 | -1.4961 | -0.2326 | -0.1256 | -0.7987 | -0.6329 |
| Net-income ineq | 0.0948*** | | -0.0661 | | -0.0078 | | -0.0081 | |
| Market-income ineq | | 0.0131 | | -0.0799** | | 0.0118 | | 0.0364 |
| Net-Sen's index (ln) | | | -1.5134*** | | | | 0.3105 | |
| Market-Sen's index (ln) | | | | -1.5055*** | | | | 0.5626 |
| Public social spending | | | -0.1204*** | -0.0827** | | | -0.0110 | -0.0212 |
| Number of disasters (ln) | 1.9085*** | 2.0165*** | 1.9308*** | 1.9436*** | 1.0771*** | 1.0716*** | 1.2160*** | 1.1685*** |
| Employment (ln) | 0.5718*** | 0.6990*** | 0.8300*** | 0.8096*** | 0.4012*** | 0.3882*** | 0.3825** | 0.3447* |
| tfp | -1.2105** | 0.0220 | 2.3183 | 2.0163 | -0.9191 | -1.2315* | -0.4055 | -0.9850 |
| Population density (ln) | -0.1306** | -0.2495*** | -0.2903*** | -0.3009*** | 0.0363 | 0.0571 | 0.0591 | 0.0963 |
| Pop in the largest city | 0.0071 | 0.0248*** | 0.0460*** | 0.0426*** | -0.0093 | -0.0115 | 0.0032 | 0.0008 |
| Time-dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Constant | 14.6831*** | 19.4964*** | 19.0098*** | 19.8845*** | 8.5274*** | 7.3476*** | 8.2734* | 4.8465 |
| Observations | 1,586 | 1,586 | 486 | 486 | 988 | 988 | 389 | 389 |
| R-squared | 0.5190 | 0.4942 | 0.5087 | 0.5101 | 0.3617 | 0.3620 | 0.3695 | 0.3706 |

*** p<0.01, ** p<0.05, * p<0.1

*B. FE estimator*

| | Human impact (ln) (9) | Human impact (ln) (10) | Human impact (ln) OECD (11) | Human impact (ln) OECD (12) | Economic impact (ln) (13) | Economic impact (ln) (14) | Economic impact (ln) OECD (15) | Economic impact (ln) OECD (16) |
|---|---|---|---|---|---|---|---|---|
| GDP per capita (ln) | -1.4386* | -1.4456* | | | -0.3589 | -0.4824 | | |
| Annual growth (ln) | -2.4032 | -2.4418 | -5.0978 | -4.9027 | -5.6300** | -6.0565** | -8.1194 | -9.2172 |
| 5-year growth (ln) | -1.1691** | -1.1681** | -1.2857 | -1.1756 | -0.2124 | -0.2982 | 0.9164 | 0.7972 |
| Net-income ineq | 0.0450 | | -0.1614 | | 0.0325 | | 0.0823 | |
| Market-income ineq | | 0.0605** | | -0.1292 | | 0.0651** | | 0.1466 |
| Net-Sen's index (ln) | | | -6.6973** | | | | 0.4848 | |
| Market-Sen's index (ln) | | | | -6.1956** | | | | 0.6994 |
| Public social spending | | | -0.0711 | -0.0508 | | | -0.1010 | -0.1348 |
| Number of disasters (ln) | 1.8467*** | 1.8388*** | 1.9774*** | 1.9701*** | 1.0019*** | 0.9988*** | 1.0864*** | 1.0787*** |
| Employment (ln) | 1.5956 | 1.8667 | 1.3255 | 1.2613 | 0.9613 | 1.3870 | 0.4902 | 1.3340 |
| tfp | 2.6105** | 2.7463** | 9.3028** | 8.5359* | 2.2010 | 2.5418* | -2.7714 | -2.3060 |
| Population density (ln) | 0.9424 | 1.3570 | 7.8879 | 7.9025 | -0.7798 | -0.2997 | 0.9413 | 1.6042 |
| Pop in the largest city | 0.0295 | 0.0322 | -0.1669 | -0.1733 | -0.0523 | -0.0552 | -0.1061 | -0.0619 |
| Time-dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Fixed-effects | YES | YES | YES | YES | YES | YES | YES | YES |
| Constant | 11.5717 | 8.5275 | 33.9775 | 29.0961 | 14.9020 | 11.5521 | 5.8954 | -5.5373 |
| Observations | 1,586 | 1,586 | 486 | 486 | 988 | 988 | 389 | 389 |
| R-squared | 0.2193 | 0.2214 | 0.2171 | 0.2163 | 0.1452 | 0.1496 | 0.1867 | 0.1948 |

*** p<0.01, ** p<0.05, * p<0.1

**Table 3: The human and economic impact of natural disasters on economic growth**

*A. OLS estimator*

| | Annual growth (ln) (1) | Annual growth (ln) (2) | Annual growth (ln) OECD (3) | Annual growth (ln) OECD (4) | 5-year growth (ln) (5) | 5-year growth (ln) (6) | 5-year growth (ln) OECD (7) | 5-year growth (ln) OECD (8) |
|---|---|---|---|---|---|---|---|---|
| Human impact (ln) | 0.0004 | 0.0004 | 0.0001 | 0.0001 | 0.0023 | 0.0023 | 0.0015 | 0.0013 |
| Economic impact (ln) | -0.0005 | -0.0005 | -0.0002 | -0.0002 | -0.0037* | -0.0036* | -0.0021 | -0.0022 |
| GDP per capita (ln) | -0.0037 | -0.0037 | | | -0.0177** | - 0.0174*** | | |
| Net-income ineq | 0.0000 | | -0.0002 | | -0.0004 | | 0.0012 | |
| Market-income ineq | | 0.0000 | | -0.0002 | | -0.0010 | | -0.0002 |
| Net-Sen's index (ln) | | | -0.0062 | | | | -0.0282** | |
| Market-Sen's | | | | -0.0066 | | | | - |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| index (ln) | | | | | | | | 0.0389*** |
| Public social spending | | | -0.0008*** | -0.0008** | | | -0.0013* | -0.0020** |
| Number of disasters (ln) | 0.0039 | 0.0039 | 0.0014 | 0.0014 | -0.0019 | -0.0022 | -0.0050 | -0.0024 |
| Employment (ln) | 0.0000 | 0.0000 | -0.0048*** | -0.0047*** | 0.0105* | 0.0098* | -0.0147*** | -0.0137*** |
| tfp | -0.0748*** | -0.0746*** | -0.0441*** | -0.0445*** | -0.3949*** | -0.3882*** | -0.4654*** | -0.4284*** |
| Population density (ln) | 0.0034*** | 0.0033*** | 0.0005 | 0.0004 | 0.0115*** | 0.0111*** | 0.0009 | -0.0002 |
| Pop in the largest city | 0.0003* | 0.0003** | 0.0000 | 0.0000 | 0.0013*** | 0.0013*** | 0.0000 | 0.0001 |
| Time-dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Constant | 0.1176** | 0.1181** | 0.1434*** | 0.1500*** | 0.6124*** | 0.6392*** | 0.8364*** | 0.9546*** |
| Observations | 996 | 996 | 348 | 348 | 859 | 859 | 295 | 295 |
| R-squared | 0.2450 | 0.2450 | 0.4477 | 0.4481 | 0.4006 | 0.4017 | 0.6596 | 0.6568 |

*** p<0.01, ** p<0.05, * p<0.1

*B. FE estimator*

| | Annual growth (ln) (9) | Annual growth (ln) (10) | Annual growth (ln) OECD (11) | Annual growth (ln) OECD (12) | 5-year growth (ln) (13) | 5-year growth (ln) (14) | 5-year growth (ln) OECD (15) | 5-year growth (ln) OECD (16) |
|---|---|---|---|---|---|---|---|---|
| Human impact (ln) | 0.0006 | 0.0005 | 0.0001 | 0.0001 | 0.0024* | 0.0023 | 0.0008 | 0.0007 |
| Economic impact (ln) | -0.0002 | -0.0003 | 0.0003 | 0.0003 | -0.0032* | -0.0033* | -0.0003 | -0.0001 |
| GDP per capita (ln) | -0.0972*** | -0.0941*** | | | -0.3946*** | -0.3804*** | | |
| Net-income ineq | 0.0025*** | | -0.0026** | | 0.0113*** | | 0.0006 | |
| Market-income ineq | | 0.0019*** | | -0.0030*** | | 0.0064*** | | -0.0040* |
| Net-Sen's index (ln) | | | -0.0737*** | | | | -0.1178* | |
| Market-Sen's index (ln) | | | | -0.0748*** | | | | -0.1402** |
| Public social spending | | | -0.0040*** | -0.0033*** | | | -0.0148*** | -0.0149*** |
| Number of disasters (ln) | 0.0070** | 0.0074** | 0.0021 | 0.0020 | 0.0037 | 0.0048 | -0.0045 | -0.0038 |
| Employment (ln) | -0.0171 | -0.0200 | -0.0592 | -0.0637* | -0.1459** | -0.1693** | -0.7161*** | -0.7273*** |
| tfp | -0.0297 | -0.0279 | 0.0536 | 0.0442 | -0.1926*** | -0.1842*** | -0.3737*** | -0.3565*** |
| Population density (ln) | -0.0171 | 0.0013 | 0.0450 | 0.0290 | 0.1703* | 0.2372** | 0.8554*** | 0.8367*** |
| Pop in the largest city | -0.0000 | -0.0002 | 0.0008 | 0.0002 | -0.0001 | 0.0001 | 0.0007 | 0.0001 |
| Time-dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Fixed-effects | YES | YES | YES | YES | YES | YES | YES | YES |
| Constant | 0.9214*** | 0.8482*** | 0.7543** | 0.8879*** | 3.0588*** | 2.8718*** | -0.0153 | 0.4732 |
| Observations | 996 | 996 | 348 | 348 | 859 | 859 | 295 | 295 |
| R-squared | 0.3304 | 0.3281 | 0.4546 | 0.4613 | 0.5686 | 0.5514 | 0.6829 | 0.6823 |

*** p<0.01, ** p<0.05, * p<0.1

**Table 4: The influence of national wealth, income inequality and social welfare on technological disaster outcomes**

*A. OLS estimator*

| | Human impact (ln) (1) | Human impact (ln) (2) | Human impact (ln) OECD (3) | Human impact (ln) OECD (4) |
|---|---|---|---|---|
| GDP per capita (ln) | -0.0217 | 0.0063 | | |
| Annual growth (ln) | -1.3062 | -1.3091 | 1.2489 | 1.0565 |
| 5-year growth (ln) | 0.0429 | 0.0951 | -0.7310 | -0.2705 |
| Net-income ineq | -0.0088 | | -0.0542** | |
| Market-income ineq | | 0.0003 | | 0.0182 |
| Net-Sen's index (ln) | | | 0.0271 | |
| Market-Sen's index (ln) | | | | 0.4866* |
| Public social spending | | | -0.0199 | -0.0099 |
| Number of disasters (ln) | 1.2438*** | 1.2228*** | 1.2834*** | 1.2228*** |
| Employment (ln) | 0.1748*** | 0.1635*** | 0.3532*** | 0.2521** |
| tfp | 0.8093** | 0.7009** | 1.5878 | 0.1957 |
| Population density (ln) | 0.0704** | 0.0820** | -0.0585 | 0.0130 |
| Pop in the largest city | 0.0107*** | 0.0088** | 0.0187** | 0.0135 |
| Time-dummies | YES | YES | YES | YES |
| Constant | 3.9249*** | 3.4420** | 3.4441 | -2.2304 |
| Observations | 1,136 | 1,136 | 337 | 337 |
| R-squared | 0.5227 | 0.5218 | 0.4378 | 0.4285 |

*** p<0.01, ** p<0.05, * p<0.1

*B. FE estimator*

| | Human impact (ln) (5) | Human impact (ln) (6) | Human impact (ln) OECD (7) | Human impact (ln) OECD (8) |
|---|---|---|---|---|
| GDP per capita (ln) | 0.3135 | 0.1648 | | |
| Annual growth (ln) | -1.2821 | -1.3060 | -0.7879 | -0.7998 |
| 5-year growth (ln) | 0.1415 | 0.1774 | -1.9608 | -1.7633 |
| Net-income ineq | -0.0249 | | -0.0346 | |
| Market-income ineq | | -0.0033 | | 0.0009 |
| Net-Sen's index (ln) | | | 1.6175 | |
| Market-Sen's index (ln) | | | | 1.7919 |
| Public social spending | | | -0.1548** | -0.1384** |
| Number of disasters (ln) | 1.2953*** | 1.2922*** | 1.4518*** | 1.4499*** |
| Employment (ln) | 0.1920 | 0.4244 | -1.1657 | -1.2492 |
| tfp | 0.4453 | 0.5624 | 0.4084 | -0.0629 |
| Population density (ln) | 0.3421 | 0.1976 | -1.5473 | -1.5631 |
| Pop in the largest city | 0.0644** | 0.0604** | 0.0598 | 0.0639 |
| Time-dummies | YES | YES | YES | YES |
| Fixed-effects | YES | YES | YES | YES |
| Constant | -0.2201 | 0.3529 | 0.1965 | -1.9316 |
| Observations | 1,136 | 1,136 | 337 | 337 |
| R-squared | 0.3206 | 0.3192 | 0.3658 | 0.3651 |

*** p<0.01, ** p<0.05, * p<0.1



**Table 5: The human impact of technological disasters on economic growth**

*A. OLS estimator*

| | Annual growth (ln) | Annual growth (ln) | Annual growth (ln) | Annual growth (ln) | 5-year growth (ln) | 5-year growth (ln) | 5-year growth (ln) | 5-year growth (ln) |
|---|---|---|---|---|---|---|---|---|

| | (1) | (2) | OECD (3) | OECD (4) | (5) | (6) | OECD (7) | OECD (8) |
|---|---|---|---|---|---|---|---|---|
| Human impact (ln) | -0.0013 | -0.0013 | 0.0001 | -0.0000 | -0.0039 | -0.0041 | -0.0036 | -0.0041 |
| GDP per capita (ln) | 0.0003 | -0.0001 | | | 0.0027 | -0.0025 | | |
| Net-income ineq | 0.0001 | | 0.0003 | | 0.0013** | | 0.0015 | |
| Market-income ineq | | -0.0003 | | 0.0002 | | -0.0001 | | 0.0001 |
| Net-Sen's index (ln) | | | -0.0035 | | | | -0.0253* | |
| Market-Sen's index (ln) | | | | -0.0044 | | | | -0.0357*** |
| Public social spending | | | -0.0008*** | -0.0010*** | | | -0.0019** | -0.0027*** |
| Number of disasters (ln) | 0.0029 | 0.0033 | -0.0022 | -0.0019 | 0.0145* | 0.0180** | 0.0011 | 0.0034 |
| Employment (ln) | 0.0029* | 0.0029* | -0.0047** | -0.0045** | 0.0035 | 0.0044 | -0.0221*** | -0.0198*** |
| tfp | -0.0484*** | -0.0449*** | -0.0789*** | -0.0750*** | -0.3995*** | -0.3800*** | -0.4421*** | -0.4067*** |
| Population density (ln) | 0.0025** | 0.0022** | 0.0008 | 0.0008 | 0.0126*** | 0.0105*** | 0.0002 | -0.0011 |
| Pop in the largest city | 0.0002 | 0.0002 | -0.0001 | -0.0001 | 0.0004 | 0.0007* | -0.0004 | -0.0003 |
| Time-dummies | YES | YES | YES | YES | YES | YES | YES | YES |
| Constant | 0.0882** | 0.1038*** | 0.1345** | 0.1418*** | 0.5206*** | 0.6045*** | 0.8199*** | 0.9369*** |
| Observations | 1,194 | 1,194 | 329 | 329 | 1,000 | 1,000 | 274 | 274 |
| R-squared | 0.1896 | 0.1908 | 0.4167 | 0.4166 | 0.3610 | 0.3576 | 0.5851 | 0.5822 |

*** p<0.01, ** p<0.05, * p<0.1

*B. FE estimator*

| | Annual growth (ln) (9) | Annual growth (ln) (10) | Annual growth (ln) OECD (11) | Annual growth (ln) OECD (12) | 5-year growth (ln) (13) | 5-year growth (ln) (14) | 5-year growth (ln) OECD (15) | 5-year growth (ln) OECD (16) |
|---|---|---|---|---|---|---|---|---|
| Human impact (ln) | -0.0010 | -0.0011 | -0.0003 | -0.0003 | -0.0030 | -0.0036 | -0.0038* | -0.0039* |
| GDP per capita (ln) | -0.0840*** | -0.0815*** | | | -0.3289*** | -0.3052*** | | |
| Net-income ineq | 0.0009* | | 0.0000 | | 0.0076*** | | 0.0060** | |
| Market-income ineq | | 0.0010** | | -0.0002 | | 0.0060*** | | 0.0010 |
| Net-Sen's index (ln) | | | -0.0257 | | | | -0.0130 | |
| Market-Sen's index (ln) | | | | -0.0252 | | | | -0.0353 |
| Public social spending | | | -0.0016 | -0.0017 | | | -0.0098*** | -0.0113*** |
| Number of disasters (ln) | 0.0057** | 0.0058** | -0.0001 | -0.0002 | 0.0305*** | 0.0318*** | 0.0066 | 0.0068 |
| Employment (ln) | -0.0282 | -0.0272 | -0.0692 | -0.0695 | -0.1652*** | -0.1724*** | -0.8459*** | -0.8674*** |
| tfp | 0.0207 | 0.0190 | -0.0073 | -0.0066 | -0.3114*** | -0.3274*** | -0.4678*** | -0.4435*** |
| Population density (ln) | 0.0394 | 0.0500 | 0.0862 | 0.0870 | 0.0457 | 0.1183 | 0.9411*** | 0.9407*** |
| Pop in the largest city | 0.0024*** | 0.0024*** | 0.0026** | 0.0026** | 0.0061*** | 0.0059*** | 0.0050 | 0.0033 |
| Time-dummies | YES | YES | YES | YES | YES | YES | YES | YES |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Fixed-effects | YES | YES | YES | YES | YES | YES | YES | YES |
| Constant | 0.5829*** | 0.5198*** | 0.0445 | 0.0453 | 3.1465*** | 2.7517*** | -1.2536 | -0.8035 |
| Observations | 1,194 | 1,194 | 329 | 329 | 1,000 | 1,000 | 274 | 274 |
| R-squared | 0.2389 | 0.2400 | 0.4024 | 0.4021 | 0.5062 | 0.5035 | 0.6786 | 0.6707 |

*** p<0.01, ** p<0.05, * p<0.1