FACULTAD ECONOMÍA Y NEGOCIOS
UNIVERSIDAD DE CHILE
DEPARTAMENTO DE ECONOMÍA

SERIE DE DOCUMENTOS DE TRABAJO

SDT 414

Climate Change and Natural Disasters

Autores:
Ramón E. López
Vinod Thomas
Pablo Troncoso

Santiago, Diciembre de 2015

sdt@econ.uchile.cl
econ.uchile.cl/publicaciones

November 30, 2015

Climate Change and Natural Disasters

Ramón E. López, Vinod Thomas and Pablo Troncoso

Ramón E. López is Professor at the Department of Economics, University of Chile. Vinod Thomas is Director-General of Independent Evaluation, Asian Development Bank. Pablo Troncoso is a lecturer at University of Chile. Financial support for this research was provided by The Asian Development Bank.

CONTENTS

ABSTRACT

Intense climate-related disasters—floods, storms, droughts, and heat waves—have been on the rise worldwide. At the same time and coupled with an increasing concentration of greenhouse gases in the atmosphere, temperatures, on average, have been rising, and are becoming more variable and more extreme. Rainfall has also been more variable and more extreme.

Is there an ominous link between the global increase of these hydrometeorological and climatological events on the one side and anthropogenic climate change on the other? This paper considers three main disaster risk factors—rising population exposure, greater population vulnerability, and increasing climate-related hazards—behind the increased frequency of intense climate-related natural disasters.

In a regression analysis within a model of disaster risk determination for 1971–2013, population exposure measured by population density and people's vulnerability measured by socioeconomic variables are positively linked to the frequency of these intense disasters. Importantly, the results show that precipitation deviations are positively related to hydrometeorological events, while temperature and precipitation deviations have a negative association with climatological events. Moreover, global climate change indicators show positive and highly significant effects.

Along with the scientific association between greenhouse gases and the changes in the climate, the findings in this paper suggest a connection between the increasing number of natural disasters and man-made emissions of greenhouse gases in the atmosphere. The implication is that climate mitigation and climate adaptation should form part of actions for disaster risk reduction.

Keywords: Climate, Natural Disasters, Climate-Hazards, Sustainable Development, Government Policy

JEL classification: Q54, Q56, Q58, C22

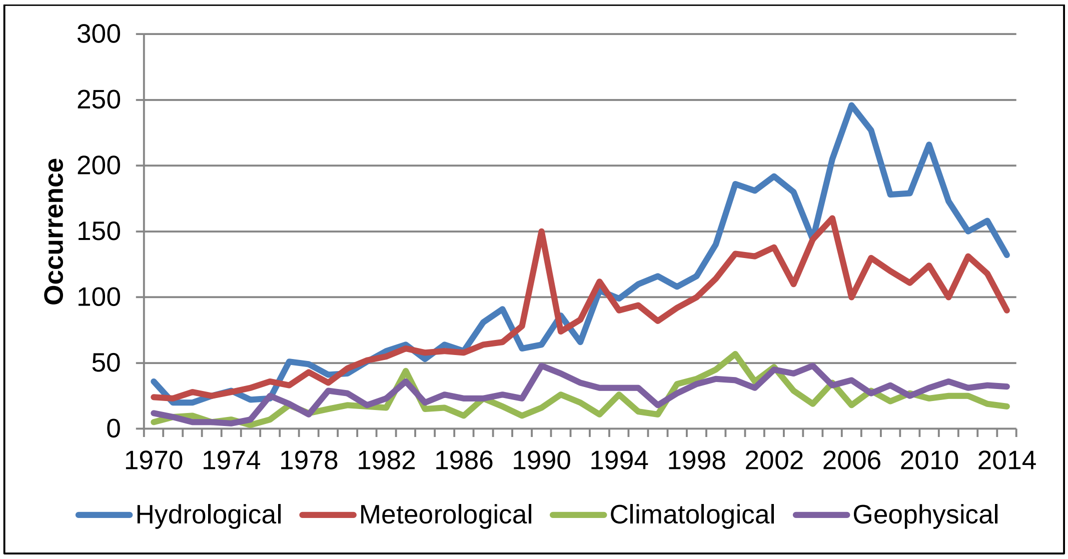
I. INTRODUCTION

The first half of this decade will be ostensibly be remembered for deadly climate-related disasters; among them, the great floods in Thailand in 2011, Hurricane Sandy in the United States in 2012, and Typhoon Haiyan in the Philippines in 2013. The year 2014 was the Earth's warmest in 134 years of recorded history (NASA GISS 2015). It is hydrometeorological (floods, storms, heat waves) and climatological disasters (droughts, wildfires) rather than geophysical ones (earthquakes, volcanic eruptions) that are on the rise.

The global increase in intense floods, storms, droughts, and heat waves has a likely and ominous link to climate change. There is a growing literature on the evidence linking anthropogenic climate change with natural disasters. [1] Drawing attention to these climate-related disasters, arguably the most tangible manifestation of global warming, could help mobilize broader climate action. And it could influence the directions taken for economic growth worldwide and pave the way to a much-needed switch to a path of low-carbon, green growth.

In the last four decades, the frequency of natural disasters recorded in the Emergency Events Database (EM-DAT) has increased almost three-fold, from over 1,300 events in 1975–1984 to over 3,900 in 2005–2014 (Figure 1). The number of hydrological and meteorological events increased sharply during this period, with the annual number of Category 5 storms tripling between 1980 and 2008 (IED 2013).[2] Although the causal relationship between climate change and natural disasters is not fully understood, we are still faced with the fact that the frequency of climate-related natural disasters is rising.

Figure 1. Global Frequency of Natural Disasters by Type (1970–2014)



Source: Authors' estimates based on data from the Emergency Event Database of the Centre for Research on the Epidemiology of Disasters. http://www.emdat.be (accessed 5 March 2015).

[1] See Thomas et al. (2013) for a more detailed discussion of the related literature.

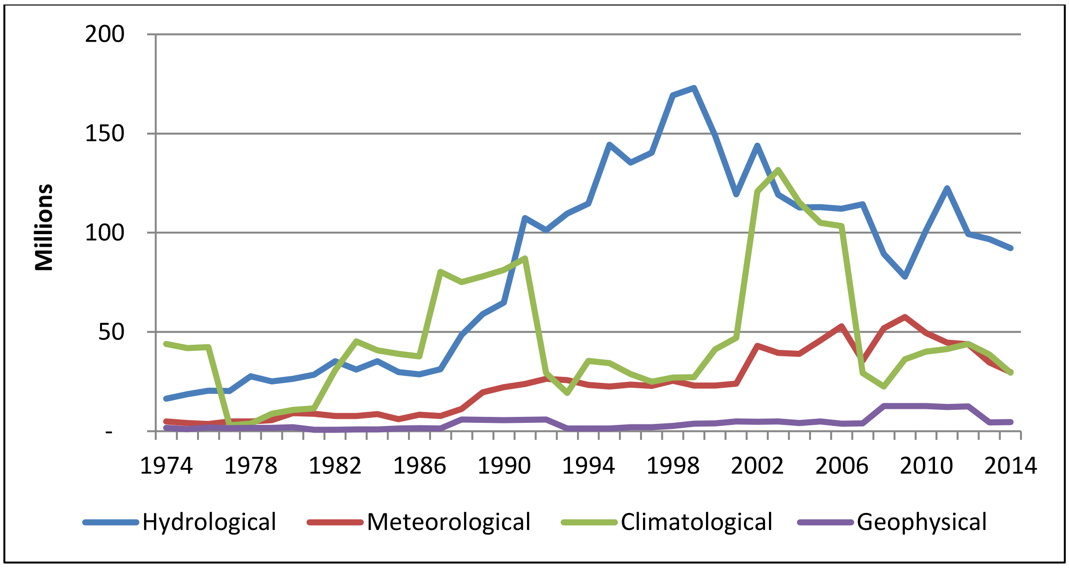
[2] Category 5 storms are the most severe and refer to hurricanes with maximum sustained wind speeds exceeding 249 km/h.

Since 2000, over 1 million people worldwide have died from natural disasters, with the cost of damage estimated at over $1.7 trillion (Guha-Sapir, Below and Hoyois 2015). However, clear trends should not be expected in natural disaster impacts. One extreme weather event like Category 5 Hurricane Sandy will muddle trends and break existing records for damages.

From 1970 to 2008, over 95% of deaths from natural disasters occurred in developing countries (IPCC 2012). In the decade 2000–2009, a third of global natural disasters and almost 80% of deaths occurred in the 40 countries that received the most humanitarian aid (Kellet and Sparks 2012).

The number of people affected by natural disasters has also been increasing. This is particularly true for hydrological disasters. Before the 1990s, 5-year averages did not reach 50 million people. This figure doubled after the 1990s, and was mostly over 100 million until 2014 (Figure 2).

Figure 2. People Affected by Natural Disasters: Global Trends (1970–2014)



Note: The number of people affected is based on a 5-year moving average.

Source: EM-DAT Database.

Global damage from natural disasters has been steadily increasing, reaching about $142 billion annually in the last 10-year period (2005–2014), a steep increase from $36 billion a year two decades ago (1985–1994) (Guha-Sapir, Below and Hoyois 2015).

Without adaptive measures, disaster damages are expected to rise to $185 billion a year from economic and population growth alone (World Bank and United Nations 2010). Probabilistic risk models estimate that the global average annual loss from earthquakes, tsunamis, cyclones, and flooding are now $314 billion (UNISDR 2015). These estimates would be even higher if climate change and urbanization were incorporated.

This study explores whether there is a significant relationship between climate change and the global increase in the frequency of intense natural disasters. As in Thomas et al. (2013), this paper considers the three main disaster risk factors—rising population exposure, greater population vulnerability, and increasing climate-related hazards—behind the global increase in frequency of intense natural hazards.

One important difference from previous work is that our empirical analysis is done in a global context covering 157 countries. Our empirical estimation also controls for two-way fixed effects which allows estimation of common-to-all global effects (over time) in addition to effects that are particular to a country. Controlling for global time effects is very important as climate phenomena in a country may be a response to global and regional climate changes on top of local temperature and precipitation changes. In addition, our analysis is extended to determine whether a relationship exists between global climate change indicators—accumulated stocks of atmospheric CO_2 and average sea temperature—and the number of global natural disasters.

Section II presents the trends and characteristics of natural disaster risk factors and is based on the Intergovernmental Panel on Climate Change (IPCC) disaster risk framework. It also establishes the analytic framework, which is built on the idea that natural disaster risk is influenced by hazards, people's exposure to those hazards, and people's vulnerability to their effects. Section III discusses the empirical framework and examines how the risk of intense climate-related disasters may be related to demographic and socioeconomic factors, climate anomalies, and global climate change indicators. It notes the significance of global effects over and above local country effects and finds that these effects have become worse throughout the time period considered. The final section presents conclusions.

II. RISING TRENDS AND THEIR CHARACTERISTICS

The IPCC (2014a) disaster risk framework sets out three linkages involving climate-related disasters. First, greenhouse gas (GHG) emissions alter atmospheric GHG concentrations and thus affect climate variables, specifically temperature and precipitation (IPCC 2007). Second, changes in the climate variables affect the frequency of climate-related hazards (IPCC 2012). Third, the frequency of climate-related hazards affects the risk of natural disasters (IPCC 2012, Stott et al. 2012).

Climate-related disaster risk is defined as the expected value of losses, often represented as the likelihood of occurrence of hazardous events multiplied by the impacts (effects on lives, livelihoods, health, ecosystems, economies, societies, cultures, services, and infrastructure), if these events occur. Disaster risks result from the interaction of three elements: (i) the hazard itself; (ii) the population exposed to the hazard (exposure); and (iii) the community's ability to withstand its impact (vulnerability) (Peduzzi et al. 2009, Thomas et al. 2013).

The anatomy of risks reveals the natural variability of hazards and also the various entry points, approaches, and considerations in managing climate-related disaster risks. Collective decisions and actions to reduce GHG emissions can slow anthropogenic climate change and its impacts. Individual and collective decisions and actions of people and societies also influence vulnerability and exposure.

A. Anthropogenic Link to Climate-Related Hazards

Since Fourier in 1824 and Tyndall in 1864, scientists have been studying the extent to which human-induced GHG emissions cause changes in the climate. While some argue that the effects of the dynamic interplay of all the underlying climate change variables are difficult to model and predict, the evidence is that the rise in global average surface temperature from 1951 to 2010 was caused by the anthropogenic increase in GHG concentrations (IPCC 2013).

The Intergovernmental Panel on Climate Change (2014b) confirms the Earth's warming atmosphere and oceans, diminishing snow and ice, and rising sea levels, among other changes The three decades starting from 1983 were likely the warmest period in the last 1,400 years in the northern hemisphere. Greenland and the Antarctic ice sheets have been losing mass and, worldwide, glaciers are shrinking (IPCC 2013).

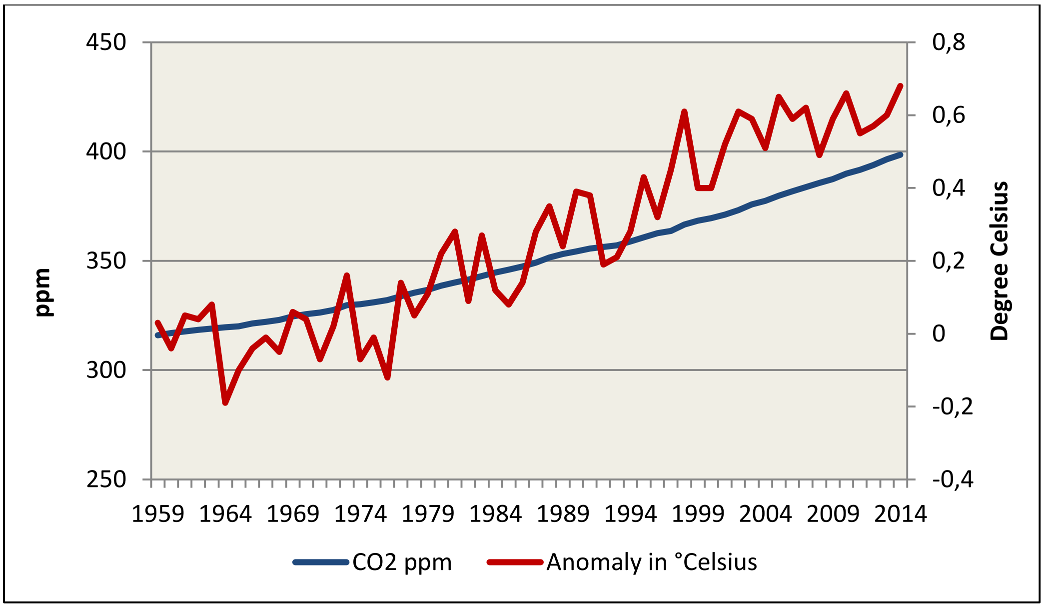
There is also a consensus in the published research. Of the more than 10,000 published research studies on climate from 1991 to 2011, 97% of the studies that express a position on anthropogenic global warming endorse it (Cook et al. 2013). In another study of 928 abstracts in refereed journals from 1993 to 2003, none of the evaluated papers disagreed that human-induced climate change had taken place (Oreskes 2004).

Greenhouse Gas Concentrations and Global Warming

Warming of the atmosphere and the ocean, changes in the global water cycle, reductions in snow and ice, the rising global mean sea level, and changes in some climate extremes are already being observed as GHG concentrations in the atmosphere continue to rise.

Humans are emitting GHGs into the Earth's atmosphere at a substantial and increasing rate—currently over 30 billion tons of carbon dioxide (CO_2) a year, along with a range of other GHGs such as methane (CH_4) and nitrous oxide (NO_2) (US EPA 2014). As a result of these emissions, GHG concentrations in the atmosphere have also been rising consistently, as have global surface temperatures (Figure 3).

Figure 3. CO_2 Atmospheric Concentrations at Mauna Loa and Global Annual Temperature Anomaly (1959–2014)



Notes: ppm = parts per million. The carbon dioxide data measured in ppm on Mauna Loa, a volcano in Hawaii, constitute the longest record of direct measurements of carbon dioxide in the atmosphere. Global annual mean surface air temperature change, in degrees Celsius, base period 1951–1980.

Sources: NASA GISS (2015), Tans (2015), and Keeling (2015).

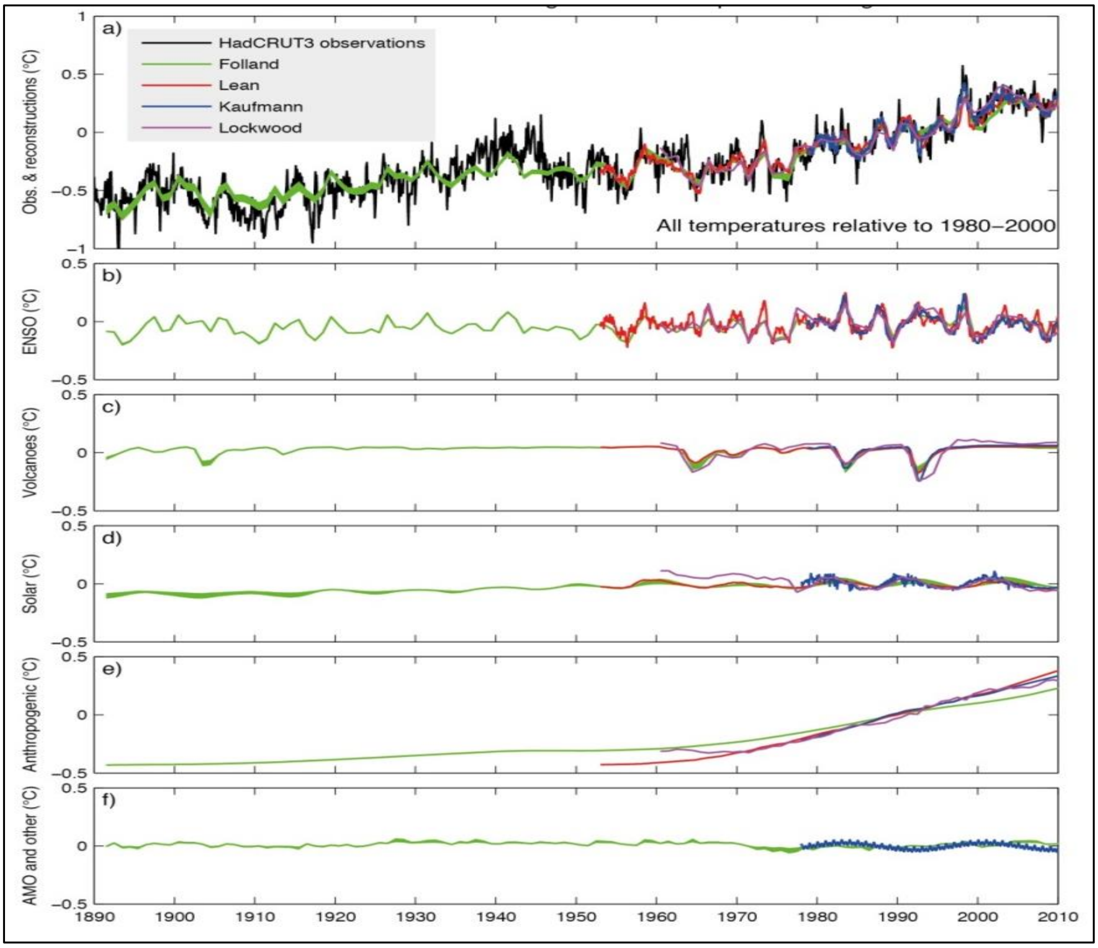
Scientists consider 450 parts per million (ppm) to be the threshold above which it will be difficult, if not impossible, to limit a temperature increase to 2°C relative to 1850–1900 levels. However, atmospheric CO_2 concentrations have already surpassed 400 ppm for three successive months in 2014. The first five months of 2015 averaged 401 ppm CO_2. If CO_2 concentrations continue to increase at a little over 2 ppm annually, as they did during 2005–

2014 (Tans 2015, Keeling 2015), the planet will exceed the 450 ppm mark in a quarter of a century. Moreover, temperature increases of 2°C above 1850–1900 levels could lead to dangerous feedback effects, such as the collapse of the Amazon ecology or thawing of permafrost (Stern 2013a). A large fraction of the anthropogenic climate change resulting from CO_2 emissions and ice sheet mass loss is irreversible on a multi-century to millennial time scale (IPCC 2013).

Increased concentrations of GHGs in the atmosphere are expected to trap more heat on Earth and to lead to a gradual increase in global average temperatures. Land and ocean temperature data show a 0.85 °C increase over 1880–2012—a warming that is extremely likely due to human influence, particularly anthropogenic GHG emissions. The 10 hottest years on record since 1880 all occurred after 1997, topped by 2014 (NOAA National Climatic Data Center 2015). For the 38th consecutive year, average annual temperatures are above the long-term average.

Detection and attribution analysis suggests that increases in global mean surface temperature were extremely likely to have been caused by anthropogenic GHG emissions. Several studies have identified and have sought to separate the different sources of global mean surface temperature variability (Figure 4) (IPCC 2013).

Figure 4. Contributions to Global Mean Temperature Change (1890–2010)



AMO = Atlantic Multi-decadal Oscillation; ENSO= El Niño-Southern Oscillation

Source: IPCC (2013)

Internal variability brought about by the Atlantic Multi-decadal Oscillation and the El Niño-Southern Oscillation have been found to be too small to have contributed to the relatively large observed warming since 1950. Similarly, the contribution of solar variability has been minimal and cannot have caused the rising temperatures. While several factors have contributed to the yearly and decadal variability of global mean surface temperatures, studies have consistently attributed most of the warming over the past 50 years to anthropogenic influence.

Global Warming and Climatic Events

Detailed studies of the 2003 European heat wave and the wintertime droughts in the Mediterranean region (1902-2010) confirm that human-induced climate change played a role in magnifying the likelihood of these hazards occurring (Stott, Stone and Allen 2004, Hoerling et al. 2012). The global record high temperature of 2014, driven by human activities, exacerbated the California 2012–2014 drought by 36%, making it the worst recorded drought in the past 1,200 years (Nuccitelli 2014).[3]

Human-induced climate change has also been linked to the increase in heat waves (Coumou and Rahmstorf 2012). There is evidence to conclude with 80% probability that the 2010 Moscow heat waves that killed 11,000 people would not have occurred without human-induced climate warming (Rahmstorf and Coumou 2011).

Evidence of anthropogenic GHG emissions contributing to the observed intensification of precipitation events was found in two-thirds of the northern hemisphere regions (Min et al. 2011). Atmospheric thermodynamics explain that the moisture-holding capacity of the atmosphere is largely influenced by temperature and pressure, and that warmer atmospheres have larger saturation vapor content. The median intensity of extreme precipitation increases with near-surface temperature at a rate of 5.9%–7.7% per degree (Westra, Alexander and Zwiers 2013). This could reach as high as 14% per degree when daily mean temperatures exceed 12° C. Even precipitation extremes that last for a short time can cause local flooding, erosion, and water damage (Lenderink and van Meijgaard 2008).

Climate change models indicate that the risk of floods occurring in England and Wales in autumn 2000 was higher by at least 20% due to 20-century anthropogenic GHG emissions (Pall et al. 2011). Case studies on three catchment regions in southeastern Australia show that a doubling of CO_2 levels would increase the frequency and magnitude of flood events with significant building damage (Schreider, Smith and Jakeman 2000). Records from Japan's automated meteorological stations situated all over the country show that the number of precipitation events exceeding 50 millimeters per hour and 80 millimeters per hour increased from the 1970s to 2013 (Japan Meteorological Agency 2014).

Dry areas are generally becoming drier and wet areas becoming wetter. With warming, more precipitation falls as rain instead of snow and snow melts earlier, further increasing the risk of runoff and flooding (Trenberth 2011).

Studies predict that a doubling of atmospheric CO_2 concentrations will triple the number of Category 5 storms (Anderson and Bausch 2006); and that for every 1°C rise in global temperature the frequency of events of the magnitude of Hurricane Katrina will increase by at least two times, and possibly by as much as seven times (Grinsted, Moore and Jevrejeva 2013). Climate models project a 3% to 5% increase in wind speed per degree Celsius increase in tropical sea surface temperatures (WMO 2006), while some projections indicate

[3] Reconstructing drought conditions, the study finds that the 2014 California drought was the most severe drought in the past 1,200 years based on the Palmer Drought Severity Index, which estimates soil moisture.

that the intensity of tropical cyclones[4] will increase by 2%–11% by 2100 (Knutson et al. 2010). With climate change, global losses from hurricanes may double (Hallegatte 2012).

Since the 1970s, the potential destructiveness of hurricanes has increased considerably and this has been shown to be highly correlated with tropical sea surface temperature. With storm lifetimes and intensities increasing by at least 50%, hurricane power dissipation has more than doubled in the Atlantic and increased by 75% in the Pacific (Emanuel 2005).

The rise in sea surface temperatures is the "main determinant of the strength of storms, the total column water vapor and the convective available potential energy" (Trenberth 2005). Hurricane Sandy—the deadliest and most destructive hurricane of the 2012 Atlantic hurricane season—was fueled by unusually warm ocean waters. Sandy produced storm surges almost 6 meters high, resulting in massive flooding that shut down the Port of New York and New Jersey for five days (Sturgis, Smythe and Tucci 2014).

Typhoon Haiyan which hit the Philippines in November 2013 formed when the sea surface temperature of the Pacific Warm Pool Region was at its highest (based on records since 1981). The sea surface temperature of the West Pacific Region was also elevated. The main trepidation, however, concerns the significant and positive increasing trend of 0.2°C per decade of the sea surface temperatures of both regions, given the correlation between sea surface temperatures and maximum winds of typhoons (Comiso, Perez and Stock 2015).

From 1975 to 2004, global hurricane data reveal that Category 4 and 5 hurricanes have almost doubled in number, from 50 every 5 years in the 1970s, to almost 90 every 5 years in the 2000s (Webster et al. 2005). The number of the weakest storms (Category 1) decreased over this period.

Global warming is also projected to increase sea levels (NOAA AOML 2015). As the sea level rises, the potential for storm surges to move further inland increases. A coastal storm surge drives large volumes of water ashore at high speed and with immense force.

The El Niño-Southern Oscillation will remain the dominant mode of yearly variability in the tropical Pacific, with global effects (IPCC 2013). But a consensus is emerging that the overall frequency of various extreme events will continue to rise due to anthropogenic global warming. The convergence of anthropogenic factors and natural variability in extreme events could be catastrophic. For instance, the increase in moisture availability is likely to intensify El Niño-related regional precipitation variability.

B. Population Exposure and Vulnerability

Exposure is the presence of people, livelihoods, ecosystems, environmental services, resources, infrastructure, and economic, social, and cultural assets in places and settings that could be adversely affected by natural hazards.

People living along cyclone tracks and near the coasts of cyclone basins expect these yearly events. Similarly, people living in low-lying coastal areas and floodplains susceptible to

[4] Tropical cyclones are areas of low atmospheric pressure over tropical and subtropical waters with a huge, circulating mass of wind with speeds of at least 119 kilometers per hour, and thunderstorms with spans of hundreds of kilometers. Aside from destructive winds, tropical cyclones can bring torrential rain, storm surges, and tornadoes that can ruin population centers, agricultural land, and metropolises. About 80 tropical cyclones form every year from seven tropical cyclone basins: Atlantic, Northeast Pacific, Northwest Pacific, North Indian, Southwest Indian, Southeast Indian, and Southwest Pacific (NOAA AOML 2015).

.

monsoon flooding are used to heavy seasonal rains. But more people and industries are now settling in these hazard-prone areas, putting themselves in harm's way.

Clearly, a climate-related hazard is unlikely to create a disaster if it strikes where there are no communities or economic activity. So an intense storm in a sparsely populated area will pose less risk than a moderate storm in a densely populated city.

While there is no homogenized dataset of global tropical cyclone landfalls, there is evidence that the increasing economic damage from tropical cyclones in recent years may be explained by the increasing wealth in locations prone to these cyclones, rather than by the increasing frequency or intensity of cyclones (Weinkle, Maue and Pielke 2012). Some suggest that, even without human-induced climate change, tropical cyclone losses and damage may double just because of increasing incomes (Mendelsohn et al. 2012).

Data from the reinsurance industry suggest that societal change—population and wealth—is sufficient to explain increasing disaster losses (Mohleji and Pielke 2014). An analysis of 22 disaster-loss studies suggests that if increases in population and capital were included in the disaster-loss equations, no loss trends can be attributed to human-induced climate change (Bouwer 2011). Some argue this may be especially true for rising urban centers with their increasing populations and the infrastructure buildup (The Economist 2012). Others suggest there are no significant trends in disaster loss and damage (Okuyama and Sahin 2009, Neumayer and Barthel 2010), as shown in hurricane losses and damages in the United States from 1900 to 2005 (Pielke et al. 2008).

Clearly, exposure is a big factor in disasters. Strong economic considerations drive that exposure. Communities and industries are built in flood-prone coastal areas because of the economic opportunities and services these areas provide, such as harbors and ports, livelihoods, and transportation. The infrastructure and market access of these areas offer comparative advantages which become more persuasive as economies become more global. An example of this is the number of megacities in regions at risk of flooding—particularly Dhaka, Kolkata, Manila, Mumbai, and Shanghai—suggesting people are making an economic judgment to establish lives and businesses in these areas despite the inherent risks.

With these megacities becoming national and regional growth centers, agglomeration economies set in, further increasing investments, in-migration, and population density. A continuing rise in human and economic exposure in high-risk megacities cannot be discounted. By 2030, Shanghai's current 23 million population is expected to rise to 31 million, and it is estimated that Dhaka will add another 10 million to its present 17 million population (UN DESA 2014). Understanding the economic decisions that have led to this situation—of more people living in harm's way—is necessary if the exposure dimensions of risks are to be managed.

Not all people and assets will be affected by hazards such as flooding and cyclones in the same way. Differences in physical, behavioral, and economic characteristics influence the propensity of people and assets to be harmed, and the lack of capacity to cope and adapt. A multidimensional concept, vulnerability to climate change, is a function of non-climatic determinants such as wealth and other demographic and socioeconomic factors (Füssel and Klein 2006).

There are opposing forces affecting people's vulnerability. On the one hand, environmental degradation has rendered many locations increasingly vulnerable to floods and storms. On the other, there has been progress in disaster risk management. With more accurate forecasting, improved early warning systems, and better evacuation procedures in place, fatalities from such events have fallen, despite their rising occurrence and damages.

The success of Bangladesh's cyclone warning system is a good example. After Cyclone Bhola, with wind speeds of 200 kilometers per hour, killed over 500,000 people in 1970, Bangladesh invested $10 billion on cyclone readiness. With the country equipped with early warning systems, disaster-resilient shelters, and embankment protection, Cyclone Sidr in 2007, with wind speeds of 250 kilometers per hour, led to a much lower death toll of 10,000 (Thorlund and Potutan 2015).

Vulnerability, like exposure, is also influenced by socioeconomic factors. The exposure–vulnerability links are quite strong, and both can either act independently or simultaneously, often creating synergies or even creating a cycle of increasing or decreasing risk.

Natural hazards are income-blind, affecting both developed and developing countries. But poorer economies are hit harder. Studies have shown how fatality rates and economic impact, and losses as a proportion of gross domestic product (GDP), are higher in developing countries (IPCC 2012) because of the higher share of impoverished populations in vulnerable urban zones, weak infrastructure, lack of basic facilities, and limited government capacity.

Poorer economies are more vulnerable because a higher share of their populations lives in marginalized urban areas with poor infrastructure. Weak government capacity and lack of basic facilities also increase susceptibility to disasters. Flash floods commonly cause more fatalities in poorer communities than in more affluent areas. Poorer segments of the population with scant resources often end up in the higher risk peripheral areas, and have less well built homes. When disaster strikes, the poor are often left with even less resources. And when livelihoods are affected, losses are further amplified, leaving people even more vulnerable.

This was vividly demonstrated in 2013 by Typhoon Haiyan, which struck the eastern Visayas, one of the poorest regions of the Philippines. Here, four out of every 10 families are poor (PSA 2013). While damage from natural disasters in that year cost the country roughly 0.9% of its national product, Haiyan-related losses amounted to 17.4% of regional product in the eastern Visayas (NEDA 2013). With very little coping capacity, many Haiyan victims are still living in tents some 18 months after the disaster.

Evidence also shows that higher educational attainment and literacy are associated with better disaster management and adaptive capacity (Brooks, Adger and Kelly 2005, Toya and Skidmore 2007).

Gender is also relevant. In the case of the 2004 Asian tsunami, there were more female deaths than males. Across age groups, children below 10 years and adults above 40 years are found to be most vulnerable (Birkmann, Fernando and Hettige 2007).

Adaptive capacity is associated with levels of governance and civil and political rights (Brooks, Adger and Kelly 2005). Countries with strong institutions (such as a strong financial sector), openness to trade, and higher levels of government spending were found to be able to better withstand initial disaster shocks (Kahn 2005, Noy 2008, Toya and Skidmore 2007).

It is vital that institutional and adaptive capacity is strengthened in cities where these are weak, but that are highly susceptible to flooding, storm surges, and tropical cyclones. Dhaka, a city regarded as being at extreme risk from climate change, is a case in point.

C. The Climate–Disaster Link

Climate change is not a necessary or a sufficient condition for disasters to occur. Mechanisms that link climate change and natural hazards cannot be held solely responsible for long-term trends in disaster losses adjusted for increases in wealth and population (Watson 2010). The association between climate change and the loss of lives and damages due to natural disasters is another point of scientific controversy. The debates linger even in cases where the climate–disaster link seems to be clearly evident. Some have argued that with data heterogeneity, trends, and attribution to anthropogenic climate forcing are extremely difficult to ascertain (Kunkel et al. 2013).

Several studies have found that income, education, and institutions shape vulnerabilities and, subsequently, natural disaster impacts (Brooks, Adger and Kelly 2005, Kahn 2005, Noy 2008, Rentschler 2013, Kellenberg and Mobarak 2008). Thomas, Albert, and Hepburn (2014) examined the importance of climate hazards (measured by climate anomalies) as a determinant of disaster risk in Asia and the Pacific, along with population exposure and vulnerability. Unlike previous econometric analyses, the authors examined the frequency of intense natural disasters as the dependent variable because it is less likely to have a reporting bias than the alternatives. Their results suggest that rising population exposure and greater climate variability play significant roles in explaining the frequency of climate disasters in the region.

Hydrometeorological disasters are strongly and positively associated with rising population exposure as well as precipitation anomalies, while climatological disasters are strongly associated with changing temperatures. Even after controlling for the effect of population exposure and vulnerability, climate factors have been a significant factor in the rise in frequency of intense hydrometeorological disasters in Asia and the Pacific in the past four decades, clearly linking climate change to disaster risks.

The evidence that it is very likely that the rising incidence of GHG emissions in the atmosphere is altering the climate system, the findings suggest a connection between the frequency of intense natural disasters observed in the region and human-induced climate change. Cyclone Nargis in Myanmar and Hurricane Sandy in the USA are clear indications that both developing and developed countries face climate-related disaster risks.

Deaths, injuries, displacements, damage, and overall disaster impact are affected by hazard intensity, exposure, and vulnerability. Awareness, preparedness, technological progress, and disaster risk reduction have clearly reduced deaths from comparable hazards. But damage from comparable events is greater in developed countries, indicating their higher-valued assets and structures, and the higher cost of rebuilding.

Climate change has already damaged the poorest and most vulnerable countries. Scientific evidence confirms the Earth's warming atmosphere and loss of glacier mass and ice sheets. Evidence has also shown that it is extremely likely that both are caused by anthropogenic GHG emissions.

III. ECONOMETRIC ANALYSIS

In this section, we examine statistically the role played by the three principal elements of natural disaster risk. The variable sought to be explained is the incidence of disasters, which is represented here by the number of disasters causing a minimum number of deaths or people affected (that is, requiring immediate assistance with basic survival needs such as food, water, shelter, sanitation, or medical assistance) in a given period. There are other measures too, for example, the level of damages in US dollars. However, measuring the impact of natural disaster in monetary terms involves a number of data issues, chiefly regarding accuracy, because of the lack of standards for comparable estimation across economies or across disasters within an economy.

A. Data and Method

Determinants of Climate-Related Disasters: Zero-Inflated Count Models

We develop econometric estimations using annual data on disasters for a sample covering most countries in the world. The model considers count data of disasters[5] by country i and year t for 1970–2013. The dependent variables are the annual frequency of intense hydrometeorological disasters (H_{it}) and the annual frequency of intense climatological disasters (C_{it}) that cause at least 100 deaths or directly affect at least 1,000 people. Intense hydrometeorological disasters relate to floods and storms while climatological disasters relate to droughts and wild fires.

The explanatory variables include W_{it}: average precipitation deviation in the country[6] (measured as departures from the average for its 30-year base climatology period 1961–1990), Z_{it}: average surface temperature deviation in the country[7] (measured as departures from the average for its 30-year base climatology period 1961-1990), and $\boldsymbol{G}_t$: global climatic change indicators including carbon dioxide accumulation in the atmosphere and sea temperature deviations from trend.[8] The study uses several proxies for vulnerability and

[5] Data for the disaster variables are from EM-DAT (Guha-Sapir, Below and Hoyois 2015). EM-DAT reports events causing at least 10 deaths, affecting at least 100 people, or prompting a declaration of a state of emergency or a call for international assistance. As in Thomas et al. (2013, 2014), we considered disasters that cause at least 100 deaths or directly affect at least 1,000 people because this approach is less likely to have a reporting bias.

[6] We use the centennial Global Precipitation Climatology Centre (GPCC) Full Data Reanalysis (Version 7.0) of monthly global land-surface precipitation based on the 75,000 stations worldwide that feature record durations of 10 years or longer. The monthly totals used in this study are on a regular grid with a spatial resolution of 1.0°x1.0° latitude by longitude (Schneider, et al. 2015).

[7] Based on HadCRUT3v (variance adjusted version), a gridded dataset of global historical surface temperature anomalies which is a collaborative dataset product of the Met Office Hadley Centre and the Climatic Research Unit at the University of East Anglia (Brohan, et al. 2005).

[8] Annual atmospheric CO_2 stock level (parts per million) is derived from in situ air measurements at the Mauna Loa Observatory, Hawaii (Latitude 19.5A°N Longitude 155.6A°W and at elevation of 3397m) (Tans n.d.). Link ftp://aftp.cmdl.noaa.gov/products/trends/co2/co2_mm_gl.txt. Average annual sea temperature deviation in Celsius is from NOAA database version 3.5.1 (00 northern -30 northern) where anomalies are based on the climatology from 1971 to 2000. Link ftp://ftp.ncdc.noaa.gov/pub/data/mlost/archive/v3.5.1/products/aravg.ann.ocean.00N.30N.asc

exposure including real gross domestic product per capita and its square as a measure of vulnerability ($\boldsymbol{V}_{it}$) and population per country as a proxy measure for exposure ($\boldsymbol{U}_{it}$).

We use a two-way fixed effects method to allow the estimation of common-to-all-countries or global time effect in addition to country and time-specific climatic and non-climatic effects. Global climate, for example, affects sea levels and their temperatures as consequences of the reduction of polar ice caps and other phenomena. As world sea levels and their temperatures increase, the effects of local temperatures and local precipitation on the magnitude and frequency of disasters in a particular country may worsen. An increase in precipitation, for example, may have a much greater effect on the magnitude and scope of flooding if the sea level is already high.

The coefficients of the common-to-all-countries time dummy variables are likely to capture the varying impact of global phenomena associated with a great number of global climatic variables. But they may not necessarily be related only to climatic variables. For example, technological and communication improvements may allow countries to improve the way they confront negative climate factors and therefore could help mitigate their impact on the size of disasters. Also, the common-to-all-countries time dummies may capture a worsening disaster effect due to increasing concentrations of population in exposed areas—a variable for which we do not have adequate data—which could be a common trend across all or most countries.

So in addition to the local climate conditions in each country we also explore the use of alternative global climate change indicators ($\boldsymbol{G}_t$): the annual atmospheric CO_2 level and the annual average sea temperature deviation, as explanatory variables. Thus, we use two approaches.

Approach 1. We use global climate indicators as a separate variable directly in the regression analysis, controlling for country-specific effects only (one-way fixed effect). These global indicators are annual atmospheric CO_2 level and annual average sea temperature deviation. We estimate these models using country fixed effects. A hypothesis is that global climate change variables exert an independent effect on disasters over and above local climatic conditions.

Approach 2. We estimate the model using a two-way[9] fixed effects method that includes controlling for both country-specific effects and common-to-all-country effects represented by a time dummy variable. This allows detection of global effects over and above local country effects.

As both dependent variables are nonnegative count values, count regression models such as the Poisson and negative binomial (NB) regression models are initially considered. The Poisson regression model (equation 1) is estimated for climatological disasters (C_{it}) because preliminary analyses show that this variable satisfies the necessary equally dispersed assumption. The NB regression model (equation 2), however, is a generalization of the Poisson regression model that allows for over-dispersion by introducing an unobserved heterogeneity term for observation i for a particular period. Hence it is used in estimating for hydrometeorological disasters (H_{it}) as likelihood ratio tests indicated the

[9] The two-way fixed effect method controls for both fixed effect by country (which are added by the command fe in Stata) and by time dummies (which are added by hand as i.year, fe). This approach can be used with negative binomial, Poisson and zero inflated models (see *Stata User's Guide*).

existence of over-dispersion. [10] We estimate the following equations using a large country sample of 157 countries. [11]

$$E[y_{it} = C_{it} | \boldsymbol{X}_{it}] = e^{\boldsymbol{X}'_{it}\boldsymbol{\beta}}$$
$$= exp(\beta_0 + \beta_1 \boldsymbol{U}_{it} + \beta_2 \boldsymbol{V}_{it} + \beta_3 W_{it} + \beta_4 Z_{it} + \beta_5 \boldsymbol{G}_t) \qquad (1)$$

$$E[y_{it} = H_{it} | \boldsymbol{X}_{it}, \varepsilon_{it}] = e^{\boldsymbol{X}'_{it}\boldsymbol{\beta}} \varepsilon_{it}$$
$$= \{exp(\beta_0 + \beta_1 \boldsymbol{U}_{it} + \beta_2 \boldsymbol{V}_{it} + \beta_3 W_{it} + \beta_4 \boldsymbol{G}_t)\} \varepsilon_{it} \qquad (2)$$

The explanatory variables $(\boldsymbol{U}_{it}, \boldsymbol{V}_{it}, W_{it}, Z_{it}, \boldsymbol{G}_t)$ are:

a. population exposure $(\boldsymbol{U}_{it})$ or the degree to which people are in harm's way

b. vulnerability $(\boldsymbol{V}_{it})$ or the population's capability to address the problem

c. the climate-related hazard, average precipitation deviation (W_{it}) and average temperature deviation (Z_{it}) in a given year

d. global climate change indicators $(\boldsymbol{G}_t)$: atmospheric CO_2 level and average sea temperature deviation

In addition, the regression also includes total population per country in the relevant year as a control variable. Even though population density is already included as an independent variable, this may not pick up the possibility that frequency of natural disasters surpassing the "intense" reporting threshold (that is, at least 100 deaths or at least 1,000 people affected due to a natural disaster) would be higher when the overall population increases.

As with most cases in count data, the count (occurrence) of intense disasters—the dependent variable—is characterized by excess zeros and over-dispersion. In particular, 67% of observations for hydrometeorological disasters and 83% for climatological disasters have zero counts. Failing to account for the prevalence of zeros in the dependent variable would be likely to result in inconsistent estimators.

There are count models that seem quite useful for dealing with the problem implied by the existence of zeros in the dependent variable (in addition to over-dispersion) in the context of both the Poisson and NB regression models. The zero-inflated (ZI) count model (introduced by Lambert, 1992 and refined by Johnson et.al., 1992) allows for modeling assuming it is possible that the zero-observed dependent variable may either correspond to countries which in a particular year had a zero probability of having a disaster as measured by the count variable and countries that had a positive probability of a disaster but that, due to random conditions in that year, experienced no disaster and consequently also had a zero dependent variable.

[10] In our dataset, the likelihood ratio (LR) tests reject the hypothesis that coefficient of dispersion (α) is equal to zero (Ho: α = 0) at 1% level of significance in all specifications involving intense hydrometeorological disasters, but not in those that involve climatological disasters.

[11] A summary of descriptive statistics for the variables used in the regressions is provided in Appendix 1.

In particular, for each country i in year t, there are two possible data generation processes—the selection of which is a result of a Bernoulli trial. The first process, which generates only zero counts, is chosen with probability ρ_i. The second process, $g(y_{it}|\boldsymbol{X}_{it})$, with probability $1-\rho_i$ generates positive counts from either a Poisson or a NB distribution. In general, we have:

$$y_{it} \sim \begin{cases} 0 & with\, probability \quad \rho_i \\ g(y_{it}|\boldsymbol{X}_{it}) & with\, probability \quad 1-\rho_i \end{cases} \tag{3}$$

Then the probability of $\{Y_{it} = y_{it}|\boldsymbol{X}_{it}\}$ can be expressed as:

$$P(Y_{it} = y_{it}|\boldsymbol{X}_{it}, \boldsymbol{I}_{it}) = \begin{cases} \rho(\gamma' \boldsymbol{I}_{it}) \quad + \{1-\rho(\gamma' \boldsymbol{I}_{it})\, g(0|\boldsymbol{X}_{it})\} & if\ y_{it} = 0 \\ \{1-\rho(\gamma' \boldsymbol{I}_{it})\, g(y_{it}|\boldsymbol{X}_{it})\} & if\ y_{it} > 0 \end{cases} \tag{4}$$

In the empirical estimation, the probability ρ_i depends on the characteristics (a subset of the explanatory variables) of country i, hence, ρ_i is written as a function of $\boldsymbol{I}'_{it}\gamma$ where $\boldsymbol{I}'_{it}$is the vector of zero-inflated covariates and γ is the vector of zero-inflated coefficients to be estimated. A probit function is specified as the zero-inflated link function—relating the product $\boldsymbol{I}'_{it}\gamma$ (which is scalar) to the probability ρ_i.

We thus estimate hydrometeorological disasters using a negative binomial zero-inflated (ZINB) regression model and climatological disasters with Poisson zero-inflated (ZIP) regression model.[12] The use of the zero inflated models reduces the likelihood of obtaining inconsistent estimators as a consequence of ignoring the existence of zeroes in the left-hand-side variable which can have heterogeneous origins.

Role of Global Climate Change Indicators: A Co-integration Analysis Approach

The estimated time dummy coefficients from the two-way fixed effects model (Approach 2) are subjected to a co-integration analysis [13] with annual data on atmospheric CO_2 deviation (with year 1970 as base level) and on average sea temperature deviation to elucidate whether time dummy coefficients and each of these global climate variables are positively correlated in a meaningful way (that is, whether they co-integrate).

First we regress y_t (the coefficients of the time dummies) on x_t (series of atmospheric CO_2 deviation and of average sea temperature deviation). This can be generally expressed as:

$$y_t = \mu + \beta x_t + \mu_t \tag{5}$$

where $\hat{\beta}$ is the predicted value of the co-integrating coefficient obtained from the ordinary least squares (OLS) estimation and μ_t is the predicted error series. The OLS estimation of equation (5) gives us an unbiased estimation about $\hat{\beta}$. However, its standard errors are inconsistent and are not normally distributed. Hence, in this case, the usual inferential procedures do not apply.

---

[12] Vuong tests revealed significant positive test statistics which favor the zero-inflated models over the standard Poisson and NB count regression models. This means that the zero-inflated method is necessary given the preponderance of zeroes of the dependent variable (Vuong 1989).

[13] See Appendix 2 for a full description of the co-integration analysis.

In order to analyze the significance of $\hat{\beta}$—the co-integrating coefficient—Engle and Granger (1987) showed that both the dependent and independent variables co-integrate if and only if there is an error correction model (ECM) for either y_t and x_t or both. To illustrate the link, let equation (5) be an equilibrium relation between two I(1) series. Since μ_t is a stationary mean zero variable, there exist a stationary autoregressive moving average (ARMA) model for μ_t. Assume for simplicity that it is an autoregressive model AR(2):

$$\mu_t = \theta_1 \mu_{t-1} + \theta_2 \mu_{t-2} + \varepsilon_t \qquad (6)$$

In particular, we can estimate equation (7) using OLS, the unrestricted autoregressive distributed lag (ADL) model, where the lag lengths are set to eliminate residual autocorrelation, an ADL(2,2) model:

$$y_t = \delta + \theta_1 y_{t-1} + \theta_2 y_{t-2} + \varphi_0 x_t + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \varepsilon_t \qquad (7)$$

To obtain the ECM form:

$$\Delta y_t = \delta + \lambda_1 \Delta y_{t-1} + k_0 \Delta x_t + k_1 \Delta x_{t-1} + \gamma_1 y_{t-1} + \gamma_2 x_{t-2} + \varepsilon_t \qquad (8)$$

where $\lambda_1 = -\theta_2, k_0 = \varphi_0, k_1 = -\varphi_2, \gamma_1 = \theta_1 + \theta_2 - 1$ and $\gamma_2 = (\varphi_0 + \varphi_1 + \varphi_2)$.

Empirically, we estimate equation (8) using the OLS method. In our case, y_t is the time dummy coefficient which represents the global impact of disasters. Hence, $\Delta y_t = y_t - y_{t-1}$. Besides, x_t represents global climate variables (atmospheric CO_2 deviation and average sea temperature deviation). The rest of the variables in equation (8) are elaborated using lags or differentials of both y_t and x_t.

From (7) and (8), the estimator of the co-integrated coefficient is given by the long-run solution expressed in equation (9):

$$\hat{\beta} = \frac{\varphi_0 + \varphi_1 + \varphi_2}{1 - \theta_1 - \theta_2} = -\frac{\hat{\gamma}_2}{\hat{\gamma}_1} \qquad (9)$$

Then, with both parameters we obtain $\hat{\beta}$ and its right standard error to analyze its significance.

B. Regression Results on Disaster Risk Factors

Table 1 shows estimates explaining the occurrence of intense hydrometeorological disasters over 1971-2013. The first and second columns show the estimates using one-way fixed effects (country effects only), including in turn as explanatory variable the annual level of atmospheric CO_2 and the annual average sea temperature deviation as an indicator of global climate effect. The third column reports the estimates of the two-way fixed effects using time dummies in addition to country fixed effects. All regressions use a negative binomial method of estimation.

The estimates are remarkably consistent. All local climate variables exhibit highly significant effects in the expected direction. Precipitation deviations exert a positive impact on the number of intense local hydrometeorological disasters. In this discussion of hydrometeorological events, temperature deviations are not included in addition to the precipitation deviations (if they were, the results would show a negative relationship with the dependent variable).

Moreover, both global climate change variables, according to one-way fixed effects, show positive and highly significant effects. However, it is possible that the global climate variables are correlated with other global variables over time which could also exert a positive impact on disasters. This would then imply that the coefficients of the global climate variables are inconsistent. This is why the second approach is important.

In the two-way fixed effects model, the time dummy variables capture any global effects whether climate-related or otherwise. The time dummy coefficients[14] are highly significant and tend to become larger over the time period. The approach is further complemented by the co-integration analysis where we elucidate whether or not there exists a meaningful relationship between the time dummy coefficients and global climate variables.

Table 1. Determinants of the Frequency of Intense HydroMeteorological Disasters
(dependent variable: frequency of intense hydrometeorological disasters,1971–2013)

Explanatory Variables	One-Way Fixed Effect		Two-Way Fixed Effect
	(1)	(2)	(3)
Exposure			
Ln (population density)	0.196***	0.196***	0.199***
	[0.0207]	[0.0232]	[0.0175]
Vulnerability			
Ln GDP per capita (constant 2005 US$)	0.219	0.257	0.241
	[0.175]	[0.207]	[0.171]
Square of Ln (GDP per capita)	-0.0169	-0.0194	-0.0184*
	[0.0119]	[0.0144]	[0.0111]
Climate hazard			
Average precipitation deviation	0.0155***	0.0178***	0.0158***
	[0.00256]	[0.00165]	[0.00117]
Global climatic indicators			
Atmospheric CO_2 level	0.0177***		
	[0.00139]		
Average sea temperature deviation		1.719***	
		[0.180]	
Population (million)	0.00221***	0.00219***	0.00219***
	[0.000919]	[0.000127]	[0.000119]
Observations	5830	5830	5830
Akaike Information Criterion (AIC)	11,187.04	11,250.81	11,076.87
Bayesian Information Criterion (BIC)	11,247.08	11,310.85	11,136.90
LR Test	462.16***	471.90***	308.74***
Vuong Test	11.49***	11.47***	11.53***

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

Source: Authors' calculations.

Table 2 shows the estimates on similar regressions for intense climatological disasters. The results on the effects of the local climate variables are not as strong or consistent as those

[14] Available from the authors upon request.

for hydrometeorological disasters. In the case of climatological events, we also include temperature deviations as an explanatory variable. Surprisingly, the temperature deviations do not show statistical significance in any of the three regressions.

Table 2. Determinants of the Frequency of Intense Climatological Disasters
(dependent variable: frequency of intense climatological disasters, 1971–2013)

Explanatory Variables	One-way fixed effect		Two-way fixed effect
	(1)	(2)	(3)
Exposure			
Ln (population density)	-0.105***	-0.0869**	-0.111***
	[0.0355]	[0.0422]	[0.0304]
Vulnerability			
Ln GDP per capita (constant 2005 US$)	-1.464***	-1.343***	-1.525***
	[0.371]	[0.201]	[0.356]
Square of Ln (GDP per capita)	0.0964***	0.0895***	0.0994***
	[0.0240]	[0.0134]	[0.0241]
Climate hazard			
Average precipitation deviation	-0.00663*	-0.00622***	-0.00619**
	[0.00352]	[0.00198]	[0.00291]
Average temperature deviation	0.0670	0.0727	-0.0915
	[0.134]	[0.0747]	[0.114]
Global climatic indicators			
Atmospheric CO_2 level	0.0146***		
	[0.00218]		
Average sea temperature deviation		1.521***	
		[0.239]	
Population (million)	0.00147***	0.00147***	0.00153***
	[0.000106]	[0.000125]	[0.000107]
Observations	4,499	4,499	4,499
Akaike Information Criterion (AIC)	4,150.778	4,155.279	4,017.679
Bayesian Information Criterion (BIC)	4,208.482	4,212.983	4,075.384
Vuong Test	4.090482***	4.161369***	3.960258***

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

Source: Authors' calculations.

However, the coefficients of both global climate variables are highly significant and with the expected signs. Also, the results of the two-way fixed effects show that most of the coefficients of the time dummy variables are significant and show increasing values over time. This permits us to use the second stage time series analysis as involved in the second approach.

These results suggest that all three factors—rising population exposure, population vulnerability, and changing climate—may play a role in explaining the global increase in the frequency of intense climate-related disasters. While climatological disasters are clearly associated with changing temperature, hydrometeorological disasters are most clearly associated with rising exposure and changing precipitation.

Since the 1980s, a similar analysis has been carried out using EM-DAT disaster data (Jennings 2011). However, this is for all types of natural disasters with factors identified, including population exposure, vulnerability, as well as other factors that affect their reporting (such as press freedom in a country). Similarly, this study points to the significance of exposure and vulnerability indicators in the disaster data, in addition acknowledges the likely effects of weather or climate change shocks, which is indicative of the changing climate as the IPCC (2012b) suggests.

Local Versus Global Climate Effects

The estimates of the coefficients of the common-to-all countries time dummies are jointly significant and most are individually significant as well. We interpret this significance as an indication that, in addition to local country factors, there are global factors affecting the frequency of climate-related natural disasters that may be related to the accumulation of carbon emissions in the atmosphere or global temperature changes. In the next section we use time series analysis to probe whether or not the values of the global effects co-integrate with the stocks of CO_2 in the atmosphere and the average sea temperature.

C. Role of Atmospheric CO_2 Accumulation on Natural Disasters

An important finding of the analysis in the previous section is that the global effects represented by the common-to-all-countries time effects were significant and explain a significant part of the frequency of both hydrometeorological and climatological disasters. That is, the global effect appears to play an important role even after accounting for local or country-specific climate conditions. More importantly, the global effect on natural disasters appears to worsen over the period of analysis. The coefficients of the time dummy variable are generally increasing over time in a statistically significant manner.

It is now necessary to test whether or not the estimated global effects on disasters are due to global climatic factors. Specifically, we implement time-series analysis to ascertain whether there is a meaningful relationship between the estimated increased global effect (represented by the increasing value over time of the coefficient of the common-to-all-countries dummy variable) and the accumulation of carbon dioxide in the atmosphere and, alternatively, the higher sea temperatures. To put this in time-series analysis jargon, do the series of CO_2 and of time dummy coefficients co-integrate?

Time Series Analysis

The first panel of Figure 5(a) shows the evolution of the estimated coefficients of the time dummy variables for hydrometeorological disasters and the CO_2 concentrations in the atmosphere during 1970–2013. As can be seen, both series exhibit upward trends over the period. The trends in the series of climatological disasters in the first panel of Figure 5(b) are similar to those in the series for hydrometeorological disasters. The series appear to be non-stationary, suggesting that any regression between the two series would yield spurious estimates of the goodness-of-fit of the regression, including the estimates of the standard errors of the estimated coefficients. In fact, formal tests suggest that the series are non-stationary.

The second panel in Figures 5(a) and 5(b) shows the series expressed in first differences, respectively, which turned out to be stationary. In other words, each of the three series (time dummy coefficients for hydrometeorological disasters, for climatological disasters, and CO_2 series) is integrated of order one.

Figure 5.Trend Relationship between Hydrometeorological and Climatological Disaster Time Dummy Values and Atmospheric CO_2 Stocks (1970-2013)

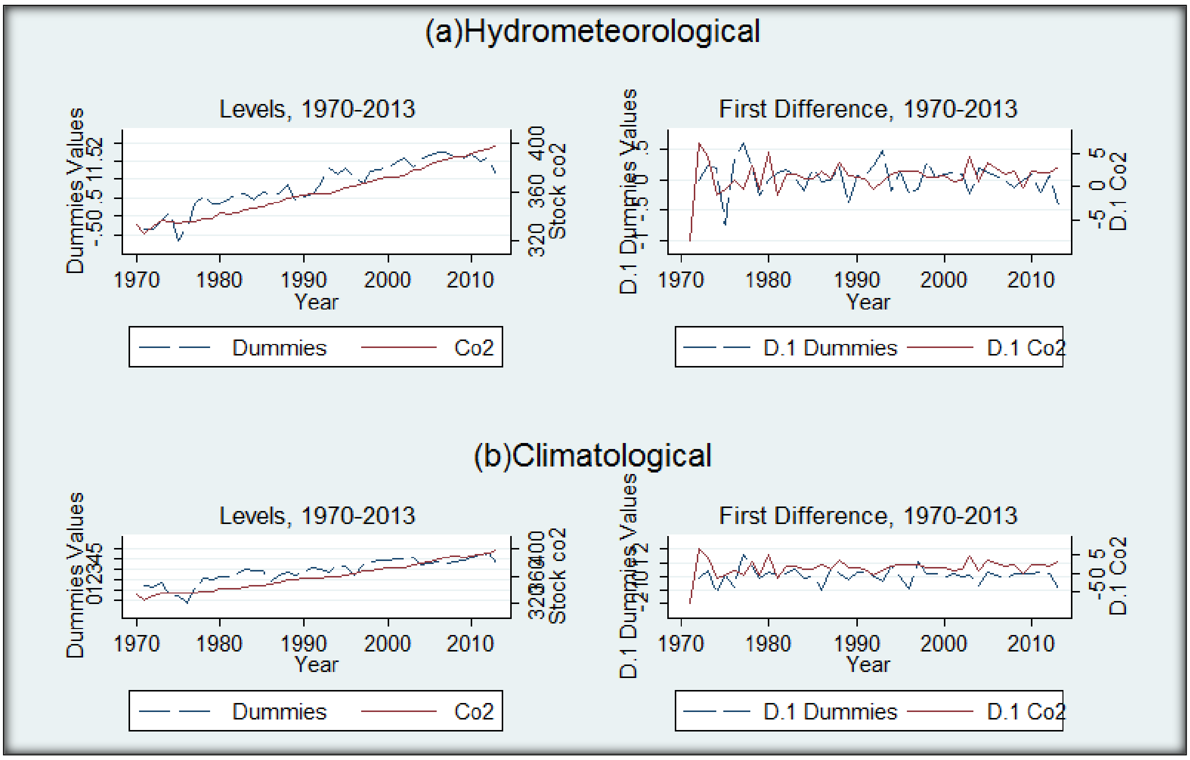
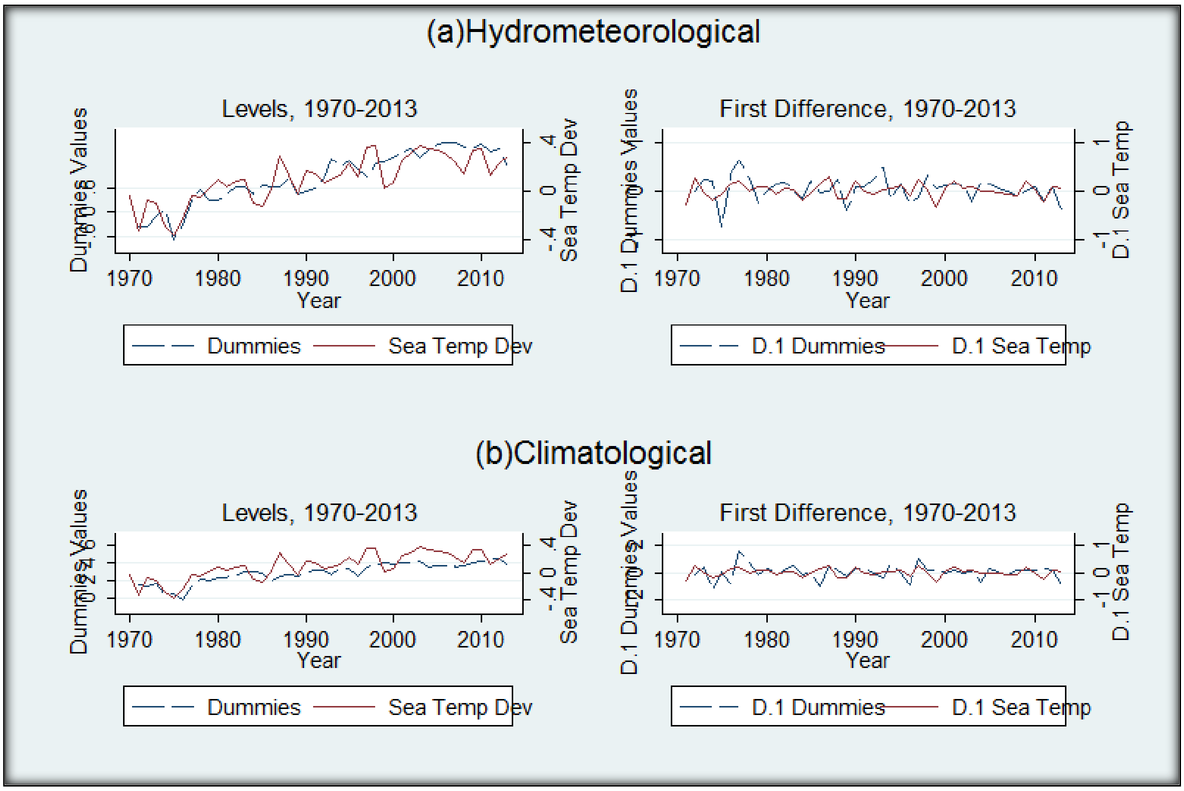


Figure 6.Trend Relationship between Hydrometeorological and Climatological Disaster Time Dummy Values and Sea Temperature Deviation (1970–2013)



As can be seen in Figures 5 and 6, the series in levels are non-stationary as both variables move together, exhibiting an ever increasing trend. However, the figures also suggest that using first differences the series might be stationary. Below we statistically test whether that is in fact the case.

In implementing the co-integration analysis, first we estimate ordinary least squares (OLS) regressions in levels. Table 3 provides these regression estimates. Since the estimated coefficients are not in general asymptotically normal, the usual inferential procedures do not apply; in particular, the estimates of the standard errors are inconsistent. However, we can use the estimated coefficients for further estimation to test for co-integration. The hypothesis to be tested is whether the predicted errors obtained from the regression estimations are stationary. Even if all individual series in levels are non-stationary, it is possible that the linear combination resulting from the estimates of each pair of series (time dummy coefficients of hydrometeorological disasters-CO_2 and of climatological disasters-CO_2) may be stationary. If they are it means that the two pairs of series co-integrate.

Table 3. OLS Regression Estimates of Time Dummy Coefficients of Intense Climate-Related Natural Disasters on Stock of Atmospheric CO_2

	Hydrometeorological	**Climatological**
Stock CO_2	0.0258***	0.0228***
	[0.00263]	[0.00481]
Constant	-8.646***	-6.374***
	[0.947]	[1.780]
Observations	43	43
Akaike Information Criterion (AIC)	15.87151	76.76739
Bayesian Information Criterion (BIC)	19.39391	80.28979
Tests for Stationarity		
Dickey-Fuller (DF)	-2.984***	-3.378***
Dickey-Fuller Generalized Least Squares (DF-GLS)	-1.491	-2.749***
1% Critical Value	-2.625	-2.625
5% Critical Value	-1.95	-1.95

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

Source: Authors' calculations based on NOAA data.

Table 3 also shows the results of tests for stationarity or co-integration using the series of predicted errors obtained from the regression estimation. Both Dickey-Fuller (DF) and Dickey-Fuller generalized least squares (DF-GLS) test whether a unit root is present in the series of the predicted errors. The DF-GLS is similar to the DF test but it also corrects for heteroscedasticity. Tabulated critical values at 1% and 5% are also shown in Table 3.[15] In the case of hydrometeorological disasters, the DF statistic allows rejection of the null hypothesis that the series have a unit root. However, the DF-GLS test indicates a failure to reject the null hypothesis which implies that hydrometeorological disasters do not appear to co-integrate with the atmospheric CO_2 stock levels.

[15] See MacKinnon, J. G. (2010).

In the case of climatological disasters, the stationary tests are more definitive (Table 4). The test for co-integration of global effects on natural disasters with CO_2 series suggests that co-integration exists.

Table 4. OLS Regression Estimates of Time Dummy Coefficients of Intense Climate-Related Natural Disasters on Sea Temperature Deviation

	Hydrometeorological	**Climatological**
Average Sea Temp Dev	2.5041***	2.6731***
	[0.2424]	[0.5149]
Constant	0.3959***	1.5529***
	[0.0541]	[0.1166]
Observations	43	43
Akaike Information Criterion (AIC)	32.08042	68.09936
Bayesian Information Criterion (BIC)	35.60282	71.62176
Tests for Stationarity		
Dickey-Fuller (DF)	-3.9809***	-3.9393***
Dickey-Fuller Generalized Least Squares (DF-GLS)	-4.1444***	-3.7532***
1% Critical Value	-2.625	-2.625
5% Critical Value	-1.95	-1.95

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

Source: Authors' calculations based on NOAA data.

The tests presented in Tables 3 and 4 are not in general considered to have sufficient power. For this reason we need to corroborate the existence of stationarity and co-integration using an error correction model as developed below.

In this study, we implemented a three-step error correction model with AR (2).

Table 5 shows the estimates of the ECM for hydrometeorological and climatological disasters-CO_2 series, respectively. While the coefficients of $CO_{2(t-1)}$ (γ_2) are always positive but not significant, the error correction coefficient, $disasters_{(t-1)}$ (γ_1), is in all cases negative and significant, confirming a dynamic process that is consistent with the existence of co-integration between the series in question. Moreover, the adjustment process is stable in all cases due to the fact that $|\gamma_1|$ <1. [16]

The satisfactory ECM estimates in conjunction with the rejection of the unit root tests and lack of rejection of the hypothesis—that the series resulting from the combination of the global effects on natural disasters and CO_2 are stationary—provide convincing evidence that the series of global effects on natural disasters and the accumulated stocks of CO_2 in the atmosphere do co-integrate. That is, a meaningful impact of CO_2 accumulation on the number of natural disasters appears to exist.

[16] We note that while $\gamma_2$coefficients are not significant they are always positive. Moreover, since these coefficients reflect short-run effects, their lack of significance may simply reflect the fact that the relationship between the series is mostly long-run in nature.

Table 5. Co-integration Analysis of Disasters-CO_2 Series: Engle-Granger Three-step Method Results

	Hydrometeorological disasters		Climatological disasters	
	Level	First Diff. (D.1)	Level	First Diff. (D.1)
Stock CO_2	0.0258***		0.0228***	
	[0.00263]		[0.00481]	
D.1 disasters $_{(t-1)}$		0.203		0.0167
		[0.180]		[0.163]
D.1 CO_2		0.0132		0.0621
		[0.0305]		[0.0500]
D.1 $CO_{2\ (t-1)}$		0.00106		-0.0242
		[0.0302]		[0.0471]
disasters $_{(t-1)}$		-0.541**		-0.473**
		[0.239]		[0.226]
$CO_{2\ (t-1)}$		0.0127		0.00917
		[0.00766]		[0.00561]
Constant	-8.646***	-4.220	-6.374***	-2.479
	[0.947]	[2.643]	[1.780]	[1.786]
Observations	43	41	43	41
AIC	15.87151	10.05464	76.76739	69.25592
BIC	19.39391	20.33607	80.28979	79.53735

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

Source: Authors' calculations based on NOAA data.

The co-integration analysis using average sea temperatures instead of CO_2 gives similar results, showing that the coefficients of the dummy variables and sea temperatures do co-integrate.

Table 6 shows the estimates of the ECM for hydrometeorological and climatological disasters- sea temperature deviation series. While the coefficients of Sea Temp Dev$_{(t-1)}$ (γ_2) are always positive and significant in hydrometeorological and climatological disasters, the error correction coefficient, *disasters*$_{(t-1)}$ (γ_1), is in all cases negative and significant thus confirming a dynamic process among them.

Table 6. Co-integration Analysis of Disasters-Sea Temperature Deviation Series: Engle-Granger Three-step Method Results

	Hydrometeorological Disasters		Climatological Disasters	
	Level	**First Diff. (D.1)**	**Level**	**First Diff. (D.1)**
Average Sea Temp Dev	2.5041***		2.6731***	
	[0.2424]		[0.5149]	
D.1 disasters *(t-1)*		0.184		0.0723
		[0.180]		[0.159]
D.1 Sea Temp Dev		1.137**		1.856***
		[0.464]		[0.601]
D.1 Sea Temp Dev *(t-1)*		-0.138		-0.288
		[0.399]		[0.609]
disasters *(t-1)*		-0.474***		-0.606***
		[0.161]		[0.195]
Sea Temp Dev *(t-1)*		1.360**		2.107***
		[0.634]		[0.733]
Constant	0.3959***	0.186***	1.5529***	0.887***
	[0.0541]	[0.0676]	[0.1166]	[0.319]
Observations	43	41	43	41
AIC	32.08042	.2094889	68.09936	57.61119
BIC	35.60282	10.49092	71.62176	67.89262

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

Source: Authors' calculations based on NOAA data.

The estimates of the γ_1 and γ_2 coefficients allow us to obtain a measure of the key coefficient $\hat{\beta}$ by using equation (9). Most importantly, the estimated standard error of $\hat{\beta}$ is unbiased and distributes according to a normal distribution, what allows us to obtain consistent statistical inference.

Significance of the results

Table 7 shows the estimated elasticities of time-dummy coefficients of hydrometeorological and climatological disasters with respect to the global climate variables. These are evaluated at the mean values (1970-2013) of the time dummy variables and global climate variables. Table 8, on the other hand, shows the simulated effects of global climate variables on disasters using mean values (1994-2013). We provide the methodology used to measure these elasticities and the simulation variation in Appendix 3.

The elasticities of time dummy coefficients for hydro-meteorological disasters for both global climate variables are much higher than those for climatological disasters. In the case of hydro-meteorological disasters, a 1% increase in the annual atmospheric CO_2 level would likely increase the average size of time dummy coefficients of hydro-meteorological disasters by approximately 13.03%.

Table 7. Estimating the Elasticities of Time dummy Coefficients of Natural Disasters with Respect to Global Climate Variables

	Hydrometeorological		Climatological	
	CO_2 Stock	**Sea Temp**	**CO_2 Stock**	**Sea Temp**
Marginal effect ($\hat{\beta}$)	0.0235	2.8692	0.0194	3.4769
Average sample value of **CO_2** level (in ppm) and Sea Temp (in ˚C) (1970-2013)	359.55	14.098	359.55	14.098
Average value of time dummy coefficients (1970-2013)	0.648	0.648	1.822	1.822
Elasticity of time dummy coefficients with respect to the global climate variables	13.03	62.42	3.83	26.90

Source: Authors' calculations

The elasticities reported in Table 7 indicate the effect of a 1% increase on the level of global climate variables on the average time dummy coefficients (obtained in the disaster regressions). The next step is to measure the effect of the changes in the time dummy coefficients on the level of disasters themselves using the estimates of the two-way fixed effect regressions. Thus the combination of these two effects yields the estimates of the net effect of global climate change on the number of disasters. This is the elasticity of disasters with respect to the global climate variables. Appendix 3 shows details of these calculations.

The elasticity of disasters reported in Table 8 show the percentage change in the average number of disasters as a likely result of a 1% percent increase on the level of global climate variables.

Using these elasticities of disasters we can simulate the effects of climate change factors on the number of disasters. The bottom-half of Table 8 shows what proportion of the variation of disasters in the decade 1994–2013 are explained by the change in global climate variables. We simulated variations on atmospheric CO_2 level. Two scenarios were considered, one for a representative country (the average of all the countries in our data) and the other for three Southeast Asian countries (Indonesia, the Philippines, and Thailand).

To illustrate, the average observed occurrence of hydrometeorological disasters in the sample for a representative country was 0.74 per year. On average, the annual increase of atmospheric CO_2 level is 2 ppm per year, equivalent to 0.5% of the current 400 ppm level. Using the elasticity of disasters to CO_2 level that is equal to 11.94 (see Appendix 3 for derivation), we estimated a simulated variation on hydrometeorological disasters.

Table 8. Explained Variation on Hydrometeorological Disasters by the Atmospheric CO_2 Concentration Level

	Representative Country	**Indonesia, Philippines, and Thailand**
	(1970-2013)	
For Elasticity of Disasters:		
Average sample values		
Atmospheric CO_2 (in ppm)	359.55	359.55
Average annual disaster occurrence	**0.480**	**4.575**
Average value of time dummy coefficients	0.648	0.648
Elasticity of disasters with respect to atmospheric CO_2 level **(***evaluated at 2009-2013 values)*	11.94	1.28
For Simulation:		
Values (2009-2013 average)		
Atmospheric CO_2 (in ppm)	394	394
Average annual disaster occurrence	0.775	7.2
Current annual increase of Atmospheric CO_2 (in ppm)	2	2
Absolute annual disaster increase	0.046	0.046
Proportional annual disaster increase	5.9%	0.64%

Source: Authors' calculations.

As shown in the Appendix 3 and in Table 8, according to our estimates, the number of hydro disasters may increase by about 5.9% per year for the average country in the sample or 0.046 more disasters per year. This implies that if the rate of increase of CO_2 level continues its current trend, in about 17 years the number of hydro disasters would double from the current average value of 0.775 to 1.55 disasters per year for the average country.

For Indonesia, the Philippines, and Thailand the effect is similar in absolute terms, increasing by about 0.05 more disasters per annum but percentage wise this amounts to *0.64% per year. This implies that if the rate of increase of CO2 continues its current trend, the number of disasters in the three Asian countries would increase by one more annual disaster every 20 years.* Thus, given the high current numbers of disasters which are almost ten times greater than for the average country in the sample, these three Asian countries would suffer much more; while the average country would increase its number of disasters by 0.74 disasters per year in 17 years of continuous increase of CO2 concentrations at the current rate, the Asian countries would increase by one disaster per year in 20 years.

Overall, the likely impact of a continuing increase in atmospheric CO_2 level is larger in absolute numbers in Indonesia, the Philippines, and Thailand than in the rest of the countries. The empirical results also suggest that sea temperature has a much greater impact on hydrometeorological disasters. Studies have shown that the rise in sea surface temperature largely determines the strength of storms. Typhoon Haiyan in 2013, for example, was formed when the sea surface temperature of the Pacific Warm Pool Region was at its highest based on the records since 1981.

Given the correlation between sea surface temperatures and maximum winds of typhoons, what really is alarming (as reported in Comiso, Perez and Stock 2015) is the significant and positive increasing trend of 0.2°C per decade of the sea surface temperatures in both West and Pacific Pool Regions.

IV. CONCLUSIONS

For 2015–2016, economists project growth rates of 3.5% for the global economy and 6% for Asia and the Pacific (IMF 2015, ADB 2015a). These growth projections do not integrate climate actions nor the impacts of climate change. The crucial question is—can the world sustain this type of growth without climate action? Can the world address climate change and switch to a low-carbon economy in time?

Domestic reforms are paramount to any country's growth prospects, but in our highly globalized world economy cross-border factors also matter. Perhaps surprisingly for some, the danger of climate change presents a greater threat than the current global economic malaise. If sustained growth is to take place, the climate challenge must be met.

Specifically, we need to strengthen disaster resilience, care more for the urban environment, and confront climate change as part of the growth paradigm. Even in the face of fluctuating oil prices, countries must commit to phasing out the use of fossil fuels and transitioning to a low-carbon economy.

Climate-related disasters have been prominent in the headlines worldwide in recent years. East and Southeast Asia top the list of the regions affected. Floods and storms have cut significantly into annual growth rates in Australia, the People's Republic of China, Indonesia, the Republic of Korea, Thailand, and Viet Nam—a trend that is set to worsen. The Philippines, often the first major landfall for typhoons arising in the western Pacific, is among the most vulnerable countries.

Multiple factors explain the mounting number and impact of disasters: people's exposure to hazards, particularly in low-lying and coastal cities; greater vulnerability from soil erosion, deforestation; and just plain overcrowding. In addition, climate hazards are becoming more menacing, which presents the most tangible reason to confront climate change as part of a development strategy. Nevertheless, scientists are cautious about linking any particular disaster to climate change, whether it is Typhoon Bopha in Mindanao, the Philippines, or Hurricane Sandy on the US East Coast. In the same way, economists are reluctant to pin higher inflation in any given month on rising money supply. But, as with inflation, the broader associations are unmistakable.

For some, the front-and-center needs of the poor heighten the dilemma of balancing growth with the environment. But that dilemma presents a false choice. Relying on a longstanding growth pattern that fuels economic momentum with environmental destruction will only aggravate climate change and it is the poor who stand to lose the most from the ravages of global warming.

The implication is that, while we must grow fast, we also need to grow differently. In essence, we need a new strategy that values all three forms of capital—physical, human, and natural. Sound growth policies have long been understood as those that expand investments in physical and human capital. But unless we also invest in natural capital, all bets are off. The 17 Sustainable Development Goals acknowledge this strong link between human well-being and environmental and ecosystem services. So what needs to be done?

First, we need to build disaster resilience into national growth strategies. Japan invests some 5% of its national budget in disaster risk reduction and has avoided much worse economic damage and deaths from disasters because of this (Government of Japan 2005).

High returns on such investments are evident even where the total spending is far less than in Japan. In the Philippines, the effects of flooding in Manila after heavy monsoon rains in August 2012 contrasted strongly with the devastation in the city from Tropical Storm Ketsana in 2009. The country has achieved vast payoffs from measures such as social media alerts, preemptive evacuations, and early warning systems. The Philippine case also highlights the benefits of the hazard maps and upgraded rain and water-level monitoring systems promoted by Project NOAH (the Nationwide Operational Assessment of Hazards).

Yet, dealing with natural disasters is still largely considered a cost to be borne after calamity strikes, rather than an investment to confront a growing threat. Disaster risk reduction accounts for just 40 cents of every $100 in total international development aid. For governments, one recommended level of spending in this respect is 1% to 2% of national budgets. But more important than the exact percentages is promoting their effective use.

Second, planners need to raise the priority of urban management as a strategic thrust. The five cities considered most vulnerable to natural hazards are all in Asia: Dhaka, Manila, Bangkok, Yangon, and Jakarta. All of them are overcrowded and in geographically fragile settings.

Massive agglomeration notwithstanding, fewer than 50% of Asians live in cities, compared with 80% in Latin America. Because further urbanization would seem inevitable, it is hard to overstate the high priority that needs to be assigned to careful physical planning, environmental care, and judicious urban management.

Third, climate action needs to be a central component of national plans. Economic growth will not be automatic if climate change is not dealt with. Adapting to the changing climate through better management of the location decisions of people and businesses and protecting the natural environment assumes greater urgency.

The poor are hit hardest by the effects of climate change. Climate adaptation, including the building of resilient communities and peoples as well as climate mitigation, including a switch to a low-carbon path, are essential parts of a poverty reduction strategy in future. No single country can make a difference in this respect. However, Asia and the Pacific, which is the region most at risk, must be a powerful voice by switching to a low-carbon path and calling on others to do the same.

We need to change our mindset on how growth is generated. Old-style growth at the expense of the environment will be self-defeating—a realization driven home by the stark reality of climate change.

Decisive action worldwide to reduce emissions is needed, but international agreements have remained elusive. Yet unilateral action can still be undertaken, especially when local gains are clear. Cutting back on black carbon emissions, especially in polluted Beijing, New Delhi, and Manila, makes for cleaner air, boosting overall health.

Disaster risk management needs to be understood as an investment, going beyond relief and reconstruction to a dual approach of prevention and recovery. Economists can facilitate this understanding by building into their calculus the role of natural hazards and climate impacts in shaping lives and livelihoods. Factoring this into the influential growth scenarios could make a big difference to policy making. Climate mitigation and adaptation need to be seen as a vital and high return part of this approach.

APPENDIX 1

Table A.1. Descriptive Statistics, 1971–2013

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
Dependent Variable: *Frequency of intense hydrometeorological disasters*	5,830	0.715	1.694	0	25
Ln (population density)	5,830	3.807	1.478	0.103	9.980
Ln GDP per capita (constant 2005 US$)	5,830	7.728	1.490	3.913	11.124
Square of Ln GDP per capita	5,830	61.950	23.753	15.311	123.752
Average precipitation deviation	5,830	-1.305	13.452	-196.409	81.774
Average temperature deviation	5,830	0.297	0.471	-1.548	2.413
Population (million)	5,830	37.714	129.983	0.041	1,357.380
Dependent Variable: *Frequency of Intense climatological disasters*	4,499	0.188	0.456	0	5
Ln (population density)	4,499	3.841	1.381	0.103	8.785
Ln GDP per capita (constant 2005 US$)	4,499	7.569	1.519	3.913	11.364
Square of Ln GDP per capita	4,499	59.596	24.158	15.311	129.131
Average precipitation deviation	4,499	-1.236	12.434	-196.409	81.774
Average temperature deviation	4,499	0.312	0.482	-1.548	2.413
Population (million)	4,499	46.732	146.609	0.044	1,357.380
Global Variables (1970–2013)					
CO_2 level	44	359.55	20.606	324.933	398.123
CO_2 deviation from level in 1970	44	26.482	20.606	-8.135	65.055
Sea temperature deviation	44	0.098	0.195	-0.374	0.378

Appendix 2

Co-integration Analysis

In a bivariate model with y_t and $x_t$variables, there exists a β such that $y_t - \beta x_t$ is I(0) even though x_t and y_t are non-stationary processes. This means that the two variables are co-integrated or have a stationary long-run relationship even though individually they are stochastic.

A vector autogression (VAR) model with ρ lags can be represented as shown in:

$$y_t = \rho_1 y_{t-1} + \rho_2 y_{t-2} + \cdots + \rho_\rho y_{t-p} + \varphi\tau_t + \varepsilon_t \qquad (1)$$

where y_t is an $kx1$ vector of I(1) variables, τ_t is a vector of deterministic variable and ε_t is an $kx1$ vector of identically and normally distributed errors with median zero and non-diagonal covariance matrix Σ. Given that the variables are co-integrated, equation (1) can be represented by an equilibrium correction model shown in (equation 2):

$$\Delta y_t = \alpha\beta y_{t-p} + \sum_{i=1}^{p-1} r\Delta y_{t-1} + \delta t + v + \varepsilon_t \qquad (2)$$

Economic importance is placed on α and β coefficients. β is an kxr matrix of co-integrating vectors that explains the long-run relationship of the variables. α is also an kxr matrix that explains long-run disequilibrium of the variables. It is important to note that for co-integration to exist, matrices α and β should have reduced rank r, where $r < k$. The identification of the cointegrating vector uses maximum likelihood method developed by Johansen (1988, 1995). The variables v and t are the deterministic trend component.

Appendix 3

Estimating the Elasticities of Disasters with Respect to Global Climate

We estimate the elasticities of disasters evaluated at the average values of the variables for the period 1970-2013. The coefficient values of the time dummy variables are related to the global climate variables as follows:

$$\mathrm{Cd_t} = \beta \cdot (\mathrm{G_t} - \overline{\mathrm{G}}) \qquad (1a)$$

Where $\mathrm{G_t}$ is atmospheric CO_2 stock level ($\mathrm{CO_{2\,t}}$) or sea temperature ($\mathrm{sea\ temp_t}$), $\overline{\mathrm{G}}$ is a fixed level of G prevailing in 1970 for CO_2 and for sea temperature its average for 1981-2000. $\mathrm{Cd_t}$ represent the coefficients of the time dummy variables. The elasticity of $\mathrm{Cd_t}$ with respect to $\mathrm{G_t}$ is:

$$\frac{\partial \ln(\mathrm{Cd_t})}{\partial \ln(\mathrm{G_t})} = \frac{\partial \mathrm{Cd_t}}{\partial \mathrm{Gt}} \cdot \frac{\mathrm{G_t}}{\mathrm{Cd_t}} = \hat{\beta} \cdot \frac{\mathrm{G_t}}{\mathrm{Cd_t}} \qquad (2a)$$

For the case of $\mathrm{CO_2}$ the estimated $\hat{\beta}$ is 0.0235, the mean sample value of $\mathrm{CO_2}$ is 359.55. and the mean sample value of $\mathrm{Cd_t}$ is 0.648. Hence, the elasticity of $\mathrm{Cd_t}$ with respect to $\mathrm{CO_{2\,t}}$when evaluated at the mean sample values is;

$$\frac{\partial \ln(\mathrm{Cd_t})}{\partial \ln(\mathrm{Gt})} = 0.0235 \cdot \frac{359.55}{0.648} = 13.03 \qquad (3a)$$

The effect of $\mathrm{Cd_t}$ on the number of hydrometeorological disasters is 0.648. Besides, the number of hydrometeorological disasters for a representative country is 0.480. Hence, given that the dummy variables are all equal to one, the elasticity of the number of disasters with respect to $\mathrm{Cd_t}$ for a representative country is,

$$\frac{\partial \ln(\mathrm{disasters_t})}{\partial \ln(\mathrm{Cd_t})} = \frac{\mathrm{Cd_t}}{\mathrm{disasters_t}} = 1.35 \qquad (4a)$$

Hence, using chain rule we have that the elasticity of disasters with respect to $\mathrm{CO_2}$ for a representative country is,

$$\frac{\partial \ln(\mathrm{disasters_t})}{\partial \ln(\mathrm{CO_{2\,t}})} = \frac{\partial \ln(\mathrm{disasters_{i,t}})}{\partial \ln(\mathrm{Cd_t})} \cdot \frac{\partial \ln(\mathrm{Cd_t})}{\partial \ln(\mathrm{CO_{2\,t}})} = 1.35 * 13.03 = 17.60 \qquad (5a)$$

Using expressions (2a) and (4a) one can measure the elasticities evaluated at the 2009-2013 average levels of the variables. In this case we have that $\mathrm{G_t} = 394$, $\mathrm{Cd_t} = 1.86$ and $\mathrm{disasters}$= 0.775. We obtain the elasticity of disasters with respect to CO_2 evaluated at 2009-2013 values that is lower than that obtained using averages for the whole period, equal to 11.94.

Conclusion. Since CO_2 levels are currently increasing by about 0.5% per year (2 ppm over a current level of 400 ppm) using the above result, we have that the number of hydro disasters may increase by about 5.9% per year. This implies that if the rate of increase of CO2 continues its current trend, in about 17 years the number of hydrometeorological disasters would double from the current average value of 0.775 to 1.55 disasters per country.

For Indonesia, Philippines, and Thailand in the same period the elasticity of $\mathrm{Cd_t}$ with respect to $\mathrm{CO_{2\ t}}$ when evaluated at the mean sample values using equation (3a) is,

$$\frac{\partial \ln(\mathrm{Cd_t})}{\partial \ln(\mathrm{CO_{2\ t}})} = 0.0235 \cdot \frac{359.55}{0.648} = 13.03 \qquad (6a)$$

The effect of $\mathrm{Cd_t}$ on the number of disasters (hydrometeorological) is 0.648. Hence, the elasticity of the number of disasters with respect to $\mathrm{Cd_t}$ for a representative country is,

$$\frac{\partial \ln(\mathrm{disasters_t})}{\partial \ln(\mathrm{Cd_t})} = \frac{\mathrm{Cd_t}}{\mathrm{disasters_t}} = 0.14 \qquad (7a)$$

Hence, using chain rule we have that the elasticity of disasters with respect to $\mathrm{CO_2}$ for a representative country is,

$$\frac{\partial \ln(\mathrm{disasters_t})}{\partial \ln(\mathrm{CO_{2\ t}})} = \frac{\partial \ln(\mathrm{disasters_{i,t}})}{\partial \ln(\mathrm{Cd_t})} \cdot \frac{\partial \ln(\mathrm{Cd_t})}{\partial \ln(\mathrm{CO_{2\ t}})} = 0.14 * 13.03 = 1.85 \qquad (8a)$$

Similarly, using expressions (6a) and (8a) one can measure the elasticities evaluated at the 2009-2013 average levels of the variables. In this case we have that $\mathrm{G_t} = 394$, $\mathrm{Cd_t} = 1.86$ and $\mathrm{disasters}$= 7.2. We obtain an elasticity of disasters with respect to CO_2 evaluated at 2009-2013 values that is lower than that obtained using averages for the whole period, equal to 1.28.

Conclusion. Since CO_2 levels are currently increasing by about 0.5% per year (2 ppm over a current level of 400 ppm) using the above result, we have that the number of hydrometeorological disasters may increase by about 0.64% per year. This implies that if the rate of increase of CO2 continues its current trend, the number of disasters in the three countries there would be one more annual disaster every 20 years.

REFERENCES

ADB. 2015. *Asian Development Outlook 2015.* Manila: Asian Development Bank.

Anderson, J., and C. Bausch. 2006. *Climate Change and Natural Disasters: Scientific Evidence of a Possible Relation Between Recent Natural Disasters and Climate Change.* Policy Brief for the EP Environment Committee (IP/A/ENVI/FWC/2005-35) Brief Number 02a/.

Barredo, J. I. 2010. No Upward Trend in Normalized Windstorm Wosses in Europe 1970–2008. *Natural Hazards and Earth System Science.* Vol 10, No. 1: 97-104.

Baskin-Gerwitz, C. 2013. The Rising Costs of Natural Disaster Insurance. *American Security Project*. 7 October. https://www.americansecurityproject.org/the-rising-costs-of-natural-disaster-insurance/.

Birkmann, J., N. Fernando, and N. Hettige. 2007. *Rapid Vulnerability Assessment in Sri Lanka.* Studies of University: Research, Counsel, Education No.7, Bonn: United Nations University, Institute for Environment and Human Security.

Bouwer, L. M. 2011. Have Disaster Losses Increased Due to Anthropogenic Climate Change? *Bulletin of the American Meteorological Society.* 92: 39-46.

Brohan, P., J.J. Kennedy, I. Harris, S.F.B. Tett, and P.D. Jones. 2005. Uncertainty Estimates in Regional and Global Observed Temperature Changes: A New Dataset from 1850. *Journal of Geophysical Research.* 111. No. D12106.

Brooks, N., W.N. Adger, and P.M. Kelly. 2005. The Determinants of Vulnerability and Adaptive Capacity at the National Level and the Implications for Adaptation. *Global Environmental Change.* 15: 151-63.

Cameron, A. C., and P. K. Trivedi. 2005. *Microeconometrics: Methods and Applications.* Cambridge University Press.

Comiso, J.C., G.J. Perez, and L.V. Stock. June 2015. Enhanced Pacific Ocean Sea Surface Temperature and Its Relation to Typhoon Haiyan. *Journal of Environmental Science and Management.* 18, No. 1: 1-10.

Cook, J., et al. 2013. Quantifying the Consensus on Anthropogenic Global Warming in the Scientific Literature. *Environmental Research Letters.* 8, No. 2.

Coumou, D., and S. Rahmstorf. 2012. A Decade of Weather Extremes. *Nature Climate Change*.

Downton, M. W., and R. A. Pielke. 2005. How Accurate are disaster loss data: The Case of US Flood Damage. *Natural Hazards.* 35, No. 2: 211-228.

Emanuel, K. 2005. Increasing Destructiveness of Tropical Cyclones over the Past 30 years. *Nature.* 436: 686-688.

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

Füssel, H-M, and R.J.T. Klein. 2006. Climate Change Vulnerability Assessments: An Evolution of Conceptual Thinking." *Climatic Change* 75, no. 3 (2006): 301-329.

Government of Japan. 2005. National Report of Japan on Disaster Reduction. *World Conference on Disaster Reduction.*

Grinsted, A., J.C. Moore, and S. Jevrejeva. 2013. Projected Atlantic Hurricane Surge Threat from Rising Temperatures. *Proceedings of the National Academy of Sciences*.

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

Hallegatte, S. 2012. Economics: The Rising Cost of Hurricanes. *Nature Climate Change.* 2: 148-49.

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

IED. 2013. *The Rise of Natural Disasters in Asia and the Pacific: Learning from ADB's Experience.* Manila: Asian Development Bank.

IMF. 2015 World Economic Outlook 2015. *IMF.* http://www.imf.org/external/pubs/ft/weo/2015/01/.

IPCC. 2007. *Climate Change 2007: Synthesis Report, Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change.* Geneva: IPCC.

IPCC. 2014a. *Climate Change 2014: Impacts, Adaptation, and Vulnerability, Contribution of Working Group II to the Fifth Assessment Report of the the Intergovernmental Panel on Clmate Change.* Cambridge and New York: Cambridge University Press.

IPCC. 2012. *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. Special Report*. Cambridge, UK and New York, USA: Cambridge University Press.

IPCC. 2013. *Summary for Policymakers. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change .* Fifth Assessment Report, Cambridge: Cambridge University Press.

IPCC. 2014b. *Summary for Policymakers. In: Climate Change 2014 Synthesis Report. Contribution of Working Groups I, II, and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Geneva: IPCC.

Japan Meteorological Agency. 2014. Climate Change Monitoring Report 2013. *Japan Meteorological Agency.* September 2014. http://www.jma.go.jp/jma/en/NMHS/indexe_ccmr.html.

Jennings, S. 2011. *Time's Bitter Flood: Trends in the Number of Reported Natural Disasters.* Oxfam GB Research Report. Oxford: Oxfam.

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

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

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

Jonkman, S.N. 2005. Global Perspectives on Loss of Human Life caused by Floods. *Natural Hazards.* 34. No. 2: 151-175.

Kahn, M.E. 2005. The Death Toll from Natural Disasters: The Role of Income, Geography, and Institutions. *The Review of Economics and Statistics.* 87. No. 2: 271-84.

Keeling, R. 6 January 2015. *Scripps Institution of Oceanography.* htttp://scrippsco2.ucsd.edu/ (accessed February 19, 2015).

Kellenberg, D.K., and A.M. Mobarak. 2008. Does Rising Income Increase or Decrease Damage Risk from Natural Disasters? *Journal of Urban Economics.* 63. No. 3 : 788-802.

Kellet, J., and D. Sparks. 2012. *Disaster Risk Reduction: Spending Where it Should Count.* Wells, Somerset: Global Humanitarian Assistance.

Knutson, T.R., et al. 2010. Tropical Cyclones and Climate Change." *Nature Geoscience.* 3 : 157-63.

Kunkel, K.E., et al. 2013. Monitoring and UnderstandingTrends in Extreme Storms: State of Knowledge. *Bulletin of the American Meteorological Society.* 94. No. 4: 499-514.

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

Lenderink, G., and E. van Meijgaard. 2008. Increase in Hourly Precipitation Extreme Beyond Expectations from Temperature Changes. *Nature Geoscience.* 1: 511-514.

Lopez, R., and A. Palacios. 2014. Why has Europe Become Environmentally Cleaner? Decomposing the Roles of Fiscal, Trade and Environmental Policies. *Environmental and Resource Economics.* 58. No. 1: 91-108.

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

Mendelsohn, R., K. Emanuel, S. Chonabayashi, and L. Bakkensen. 2012. The Impact of Climate Change on Global Tropical Cyclone Damage. *Nature Climate Change.* 2 : 205-9.

Min, S.K., X. Zhang, F.W. Zwiers, and G.C. Hegerl. 2011 Human Contributions to More Intense Precipitation Extremes. *Nature.* 470: 378-81.

Mohleji, S., and R. Jr. Pielke. 2014. Reconciliation of Trends in Global and Regional Economic Losses from Weather Events: 1980–2008. *Natural Hazards Review.* 15, No. 4: 04014009.

NASA GISS. 16 January 2015. *GISS Surface Temperature Analysis (GISTEMP).*. http://data.giss.nasa.gov/gistemp/tabledata_v3/GLB (accessed February 2, 2015).

NEDA. 2013. *Reconstruction Assistance on Yolanda.* Pasig City, Philippines: National Economic and Development Authority.

Neumayer, E., and F. Barthel. 2010. Normalizing Economic Loss from Natural Disasters: A Global Analysis. *Global Environmental Change.* 21: 13-24.

NOAA AOML. 1 June 2015. *Frequently Asked Questions*. http://www.aoml.noaa.gov/hrd/tcfaq/tcfaqHED.html (accessed June 24, 2015).

NOAA National Climatic Data Center. January 2015. State of the Climate: Global Analysis for Annual 2014. *NOAA National Climatic Data Center.* http://www.ncdc.noaa.gov/sotc/global/201413 (accessed June 11, 2015).

NOAA National Weather Service. 7 April 2011. *JetStream-Online School for Weather.* http://www.srh.noaa.gov/jetstream/tropics/tc_basins.htm (accessed June 24, 2015).

Noy, I. 2008. The Macroeconomic Consequences of Disasters. *Journal of Development Economics.* 88: 221-31.

Nuccitelli, D. 2014. California Just Had its Worst Drought in over 1200 Years, as Temperatures and Risks Rise. *The Guardian*. 8 December.

Okuyama, Y., and S. Sahin. 2009. *Impact Estimation of Disasters: A Global Aggregate for 1960 to 2007.* Policy Research Working Paper 4963, World Bank, GFDRR and International University of Japan.

Oreskes, N. 2004. The Scientific Consensus on Climate Change. *Science.* 306. No. 5702: 1686.

Pall, P., et al. 2011. Anthropogenic Greenhouse Gas Contribution to Flood Risk in England and Wales in Autumn 2000. *Nature.* 470: 382-85.

Peduzzi, P., H. Dao, C. Herold, and F. Mouton. 2009. Assessing Global Exposure and Vulnerability towards Natural Hazards: The Disaster Risk Index. *Natural Hazards and Earth Systems Sciences.* 9: 1149-1159.

Pielke, R.A., J. Gratz, C.W. Landsea, D. Collins, M. Saunders, and R. Musulin. 2008. Normalized Hurricane Damage in the United States:1900-2005. *Natural Hazards Review* 9: 1-29.

Prevention Web. 2015a. India's Heatwave a Lesson for Sendai Framework (News and Announcements). *Prevention Web.* 12 June.

http://www.preventionweb.net/english/professional/news/v.php?id=44814 (accessed June 22, 2015).

Prevention Web. 2015b. Vanuatu: Disaster Preparedness Saved Lives - UNDP (News and Announcements). 26 May. http://www.preventionweb.net/english/professional/news/v.php?id=44535&utm_source=pw_search&utm_medium=search&utm_campaign=search (accessed June 22, 2015).

PSA. 2013. Poverty Statistics-Data and Charts. *Philippine Statistics Authority-National Statistical Coordination Board.* 9 December. http://nap.psa.gov.ph/poverty/dataCharts.asp (accessed July 27, 2015).

Rahmstorf, S., and D. Coumou. 2011. Increase of Extreme Events in a Warming World. *Proceedings of National Academy of Sciences of the United States of America.* 17905–17909.

Raschky, P.A. 2008. Institutions and the Losses from Natural Disasters. *Natural Hazards and Earth System Science.* 8. No. 4: 627-634.

Rentschler, J.E. 2013. *Why Resilience Matters: The Poverty Impacts of Disasters.* World Bank Policy Research Working Paper No. 6699. Washington, DC: World Bank,.

Schneider, U., A. Becker, P Finger, A. Meyer-Christoffer, B. Rudolf, and M. Ziese. 2015. *GPPC Full Data Reanalysis Version 7.0 at 1.0°: Monthly Land-Surface Precipitation from Rain-Gauges built on GTS-based and Historic Data.* Frankfurt: Global Precipitation Climatology Centre.

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

Stern, N. 2013. *Ethics, Equity and the Economics of Climate Change. Paper 1: Science and Philosophy.* Working Paper, Leeds and London: Centre for Climate Change Economics and Policy.

Stott, P.A., D.A. Stone, and M.R. Allen. 2004. Human Contribution to the European Heatwave of 2003. *Nature.* 432: 610-14.

Stott, P.A., et al. 2012. Attribution of Weather and Climate-Related Extreme Events. WCRP Position Paper on ACE http://library.wmo.int/pmb_ged/wcrp_2011-stou.pdf.

Sturgis, L.A., T.C. Smythe, and A.E. Tucci. 2014. *Port Recovery in the Aftermath of Hurricane Sandy: Improving Port Resiliency in the Era of Climate Change.* Washington, DC: Center for a New American Security.

Tans, P. n.d. *NOAA Earth System Research Laboratory.* www.esrl.noaa.gov/gmd/ccgg/trends/.

—. *NOAA/ESRL.* January 6, 2015. www.esrl.noaa.gov/gmd/ccgg/trends/ (accessed February 19, 2015).

The Economist. 2012. Counting the Cost of Calamities. *The Economist*. January 14.

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

Thomas, V., J.R.G. Albert, and R.T. Perez. 2013. *Climate-Related Disasters in Asia and the Pacific.* ADB Economics Working Paper No. 358. Manila: ADB.

Thorlund, A.C., and G. Potutan. 2015. Bangladesh Forges Ahead on Recovery. *UNISDR.* 19 June. http://www.unisdr.org/archive/44888 (accessed July 2, 2015).

Toya, H., and M. Skidmore. 2007. Economic Development and the Impacts of Natural Disasters. *Economic Letters* 94. No. 1: 20-25.

Trenberth, Kevin E. 2011. Changes in Precipitation with Climate Change. *Climate Change Research.* 47: 123-138.

Trenberth, Kevin E. 2005. Uncertainty in Hurricanes and Global Warming. *Science.* 308 : 1753-1754.

UN DESA. 2014. *World Urbanization Prospects: The 2014 Revision.* New York: UN Department of Economic and Social Affairs.

UNESCAP. 2015. *Disasters in Asia and the Pacific: 2014 Year in Review.* Bangkok: UNESCAP.

UNISDR. 2015. Global Assessment Report on Disaster Risk Reduction 2015. Making Development Sustainable: The Future of Disaster Risk Management. Geneva..

United States Environmental Protection Agency. 2014. *Climate Change.* Washington, DC. http://www.epa.gov/climatechange/.

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

Watson, R. 2010. The IPCC Needs to Change, But the Science Remains Sound. *Yale Environment 360 Environment Forum.* 25 February. http://e360.yale.edu/feature/the_ipcc_needs_to_change_but_the_science_remains_sound/2245/.

Webster, P.J., G.J. Holland, J.A. Curry, and H.R. Chang. 2005. Changes in Tropical Cyclone Number, Duration and Intensity in a Warming Environment. *Science.* 309 : 1844-46.

Weinkle, J., R. Maue, and R. Pielke. 2012. Historical Global Tropical Cyclone Landfalls. *Journal of Climate.* 25: 4729-35.

Westra, G.S., L.V. Alexander, and F.W. Zwiers. 2013. Global Increasing Trends in Annual Maximum Daily Precipitation. *Journal of Climate.* 26. No. 11.

WMO. Statement on Tropical Cyclones and Climate Change. *Sixth WMO International Workshop on Tropical Cyclones.* Geneva: World Meteorological Organization. 2006.

World Bank and United Nations. 2010. *Natural Hazards, UnNatural disasters : The Economics of Effective Prevention.* Washington, DC: IBRD/The World Bank.

World Bank. 2011. *Guide to Climate Adaptation in Cities.* Washington, DC: World Bank .

World Bank. 2013. *Turn Down the Heat: Climate Extremes, Regional Impacts, and the Case for Resilience.* Washington, DC: World Bank.

Global Increase in Climate-Related Disasters

Intense climate-related natural disasters—floods, storms as well as droughts and heat waves have been on the rise worldwide. Is there an ominous link between the global increase of these hydrometeorological and climatological events on the one side and anthropogenic climate change on the other? This paper considers three main disaster risk factors—rising population exposure, greater population vulnerability, and increasing climate-related hazards—behind the increased frequency of intense climate-related natural disasters. All are positively linked—with precipitation positively associated with hydrometeorological events and negatively associated with climatological events. Global climate change indicators also show positive and highly significant effects.