Topical Paper

Development Effectiveness, Natural Disasters, and Climate Change

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Raising development impact through evaluation

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Development Effectiveness, Natural Disasters, and Climate Change

Note: In this report, "$" refers to US dollars

Director General	M. Taylor-Dormond, Independent Evaluation Department (IED)
Team leader	V. Thomas, former Director General, IED
Team members	G. Kilroy, Evaluation Specialist, IED
	R. Lumain, Senior Evaluation Officer, IED
	M.C. Malilay, Evaluation Assistant, IED
	H. van Rijn, Principal Evaluation Specialist, IED

Abbreviations

ADB	–	Asian Development Bank
CO_2	–	carbon dioxide
ECM	–	error correction model
GDP	–	gross domestic product
GHG	–	greenhouse gas
ppm	–	parts per million
TVCE	–	time-varying country-specific effect

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Acknowledgments

Under the guidance of Vinod Thomas, former Director General, Independent Evaluation Department, and with the final approval of Marvin Taylor-Dormond, Director General, Independent Evaluation Department, this working paper was prepared by a team comprising Hans van Rijn, Garrett Kilroy, Renato Lumain, Ma. Catherine Malilay, and consultant Alexis Arthur Garcia. Alastair McIndoe edited the paper.

Executive Summary

The impacts of natural disasters are seldom factored into the determinants of development effectiveness. This is partly because these calamities have been considered to be purely natural phenomena outside the scope of policy interventions. As a result, relief and reconstruction are taken into account, but the need for prevention and preemptive action is underemphasized.

This way of looking at natural disasters needs to change because human factors are an increasingly significant contributor to their frequency and intensity, as this topical paper shows. In disaster risk management, preventive measures need to play an important role, along with responses in recuperation, if development gains are to be protected.

Evaluations by the Asian Development Bank's (ADB's) Independent Evaluation Department (IED 2012 and 2013) of ADB's financing to deal with natural disasters in Asia and the Pacific region shed light on the effectiveness of projects implemented to respond to a variety of these calamities. A report from the World Bank's Independent Evaluation Group (IEG 2006) did the same for the world's regions. Both evaluations highlighted the crucial role of prevention in dealing with hazards of nature.

They also made the case that the underlying causes of the rising incidence of these events and their consequences need further research to understand the extent of their effect on development. A key question that needs to be addressed is whether climate change is a critical factor making climate-related disasters (floods, storms, droughts, and heat waves) more intense and more frequent. Establishing a clear association, if not causality, will be vital to support more preventive steps, including climate mitigation and adaptation. Answering this question became an agenda for continuing evaluative research, whose findings form the basis of this topical paper. A working paper (Thomas and Lopez 2015) and a background paper (Lopez 2016) reported on initial analysis of this question. This paper presents further conclusions and implications for development interventions.

The analysis suggests a causal relationship between carbon dioxide accumulation in the atmosphere and the frequency of disasters. In practical terms, this equates to about one additional major annual disaster in the world that can be attributed to the observed annual increases of carbon dioxide accumulation. There is also evidence of a negative impact on per capita gross domestic product (GDP) growth in a business-as-usual scenario in which global climatic indicators continue to deteriorate at recent rates. This means that in 20 years, the average rate of per capita GDP growth would be reduced by 1.5% just as a consequence of increased climate-related disasters.

The global increase in intense floods, storms, droughts, and heat waves has profound implications for development interventions, particularly for Asia and the Pacific—the region most at risk. While global efforts are essential, the region must be at the forefront of switching to a low-carbon path and calling on other countries to do the same. In growing fast, we also need a strategy to grow differently in a way that values all three forms of capital—physical, human, and natural.

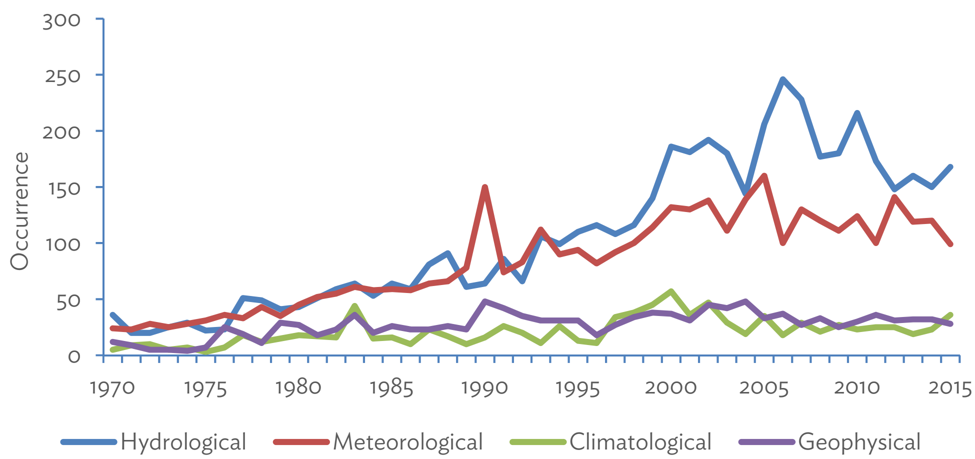
Three essential elements for this strategy are proposed. First, disaster resilience needs to be built into national growth strategies, both for prevention and recovery. The returns on such investments have already been clearly demonstrated in countries with the foresight to adopt this strategy. Second, policymakers need to raise the priority of urban management as a strategic thrust. Asia's growth has been characterized by increasing urbanization, and many of its major cities are overcrowded and in vulnerable geographic settings. Third, climate action needs to be a central component of national plans, including the building of resilient communities and peoples, and climate mitigation.

CHAPTER 1

Introduction

1. The frequency of natural disasters recorded in the Emergency Events Database has risen from over 1,300 events in 1975–1984 to over 4,000 in 2005–2015 (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).[1] 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, 1970–2015



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 9 March 2016).

2. The global increase in intense floods, storms, droughts, and heat waves has a likely and ominous link to climate change. The literature is growing on the evidence linking anthropogenic climate change with natural disasters.[2] Drawing attention to climate-related disasters, arguably the most tangible manifestation of global warming, could help mobilize broader climate action.[3] Doing this would be positive for

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[1] Hydrometeorological events include floods, storms, and heat waves. Droughts and wildfires are classified as climatological events; earthquakes and volcanic eruptions are classified as geophysical events. Category 5 storms are the most severe, and refer to hurricanes with maximum sustained wind speeds exceeding 249 kilometers per hour.

[2] See Thomas, Albert, and Hepburn (2014) for more detailed discussion of related literature.

[3] Independent Evaluation Department. 2016. *Topical Paper: Mitigating the Impacts of Climate Change and Natural Disasters for Better Quality Growth*. Asian Development Bank. Manila. Thomas V. 2017. *Climate Change and Natural Disasters: Transforming Economies and Policies for a Sustainable Future.* Asian Development Bank. Manila. (forthcoming).

development and it could influence the directions taken for economic growth worldwide, and pave the way to a much-needed path of green growth.

3. Since 2000, over 1 million people worldwide have died from natural disasters, with damages estimated at over $1.7 trillion, according to the Emergency Events Database (EM-DAT).[4] However, clear trends should not be expected in natural disaster impacts (Thomas and Lopez 2015). One extreme weather event like Category 5 Hurricane Sandy will muddle trends and break existing records for damages.

4. 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).

5. The number of people affected by natural disasters has also been increasing, particularly for hydrological disasters. Before the 1990s, 5-year averages did not reach 50 million people, but this figure doubled after the 1990s and was mostly over 100 million since then. Global damage from natural disasters has been steadily increasing, and is estimated at $145 billion annually in the last 10-year period (2005–2014), perhaps five times the annual estimate 2 decades ago (Thomas and Lopez 2015).

6. 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). Risk models estimate the global average annual loss from earthquakes, tsunamis, cyclones, and flooding at $314 billion (UNISDR 2015). These estimates would be even higher if climate change were incorporated.

[4] http://www.emdat.be

CHAPTER 2

Rising Trends and Characteristics

7. The Intergovernmental Panel on Climate Change's disaster risk framework sets out three links involving climate-related disasters (IPCC 2014a). First, greenhouse gas (GHG) emissions alter atmospheric GHG concentrations and thus affect climate variables, specifically temperature and precipitation. Second, changes in climate variables affect the frequency of climate-related hazards (IPCC 2012). And third, the frequency of climate-related hazards affects the risk of natural disasters (Stott et al. 2012).

8. 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: the hazard itself, the population's exposure to the hazard, and a community's vulnerability or its ability to withstand the impact of a hazard (Peduzzi et al. 2009).

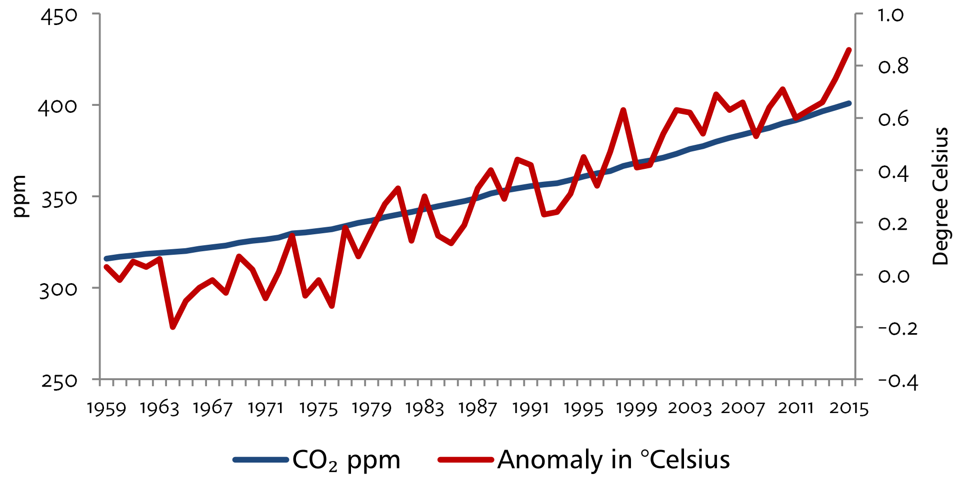
A. Anthropogenic Link to Climate-Related Hazards

9. The Intergovernmental Panel on Climate Change (IPCC) confirms the Earth's warming atmosphere and oceans, diminishing snow and ice, and rising sea levels, among other climate changes (IPCC 2014b). The three decades starting from 1983 were likely the warmest 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.

10. Published research has reached a consensus on the anthropogenic link to climate-related hazards. 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 a 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).

11. 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 other GHGs (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 2).

Figure 2: Carbon Dioxide Atmospheric Concentrations at Mauna Loa and Global Annual Temperature Anomalies, 1959–2015



CO_2 = carbon dioxide, ppm = parts per million.
Note: The CO_2 data measured in ppm on Mauna Loa, a volcano in Hawaii. Global annual mean surface air temperature change in degrees Celsius, base 1951–1980.
Source: NASA GISS 2016.

12. 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 degrees Celsius relative to 1850–1900 levels. However, atmospheric CO_2 concentrations have already surpassed 400 ppm, first in early 2014 and then for the first 10 months of 2016. The first 8 months of 2016 averaged 405 ppm CO_2. If CO_2 concentrations continue to increase at a little over 2 ppm annually, as they did during 2005–2014, the planet will exceed the 450 ppm in a quarter of a century.

13. Temperature increases of 2 degrees Celsius above 1850–1900 levels could lead to dangerous feedback effects, such as the collapse of the Amazon ecology or permafrost thawing (Stern 2013). A large fraction of the anthropogenic climate change resulting from CO_2 emissions and ice-sheet-mass loss is irreversible on a multicentury to millennial timescale (IPCC 2013).

14. 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 (Hoerling et al. 2012). The 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).[5] Human-induced climate change has also been linked to the increase in heat waves (Coumou and Rahmstorf 2012). There is evidence to conclude with a high probability that the 2010 Moscow heat waves that killed 11,000 people would not have occurred without human-induced climate warming.

15. 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 20th century anthropogenic GHG emissions (Pall et al. 2011). Case studies on three catchment regions in

[5] 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.

southeastern Australia show that a doubling of CO_2 levels would increase the frequency and magnitude of flood events, causing significant damage to buildings (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).

16. 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 degree Celsius 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 in tropical sea surface temperatures (WMO 2006). Some projections indicate that the intensity of tropical cyclones will increase by 2% to 11% by 2100 (Knutson et al. 2010).[6]

17. 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 5 days (Sturgis, Smythe, and Tucci 2014).

18. 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 degrees Celsius per decade of the sea surface temperatures of both regions, given the correlation between sea surface temperatures and maximum winds of typhoons.

B. Population Exposure and Vulnerability

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

20. 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

[6] 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).

human-induced climate change (Bouwer 2011). Some argue this may be especially true for rising urban centers with their increasing populations and infrastructure buildup (*The Economist* 2012). Others suggest there are no significant trends in disaster loss and damage (Neumayer and Barthel 2010); for example, as shown in hurricane losses and damages in the United States from 1900 to 2005.

21. 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 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 inherent risks.

22. 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 17 million population (UN DESA 2014). Understanding the economic decisions leading to this situation—more people living in harm's way—is necessary if the exposure dimensions of risks are to be managed.

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

24. The success of Bangladesh's cyclone warning system is a good example. After Cyclone Bhola, with wind speeds of 200 kilometers per hour, killed 300,000– 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, caused a much lower death toll of 10,000 (Thorlund and Potutan 2015).

25. 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.

26. 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.

27. This was demonstrated in 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 were still living in tents some 18 months after the disaster.

28. Evidence also shows that higher educational attainment and literacy are associated with better disaster management and adaptive capacity (Toya and Skidmore 2007). In the 2004 Asian tsunami, there were more female deaths than males which gives relevance to gender. Across age groups, children below 10 years and adults above 40 are found to be the most vulnerable (Birkmann, Fernando, and Hettige 2007).

C. The Climate–Disaster Link

29. Several studies find that income, education, and institutions shape vulnerabilities and, subsequently, natural disaster impacts (Brooks, Adger, and Kelly 2005, for example). Thomas, Albert, and Hepburn (2014) examined the importance of climate hazards as a determinant of disaster risk in Asia and the Pacific, along with population exposure and vulnerability.

30. Unlike previous econometric analyses, these 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 (Thomas and Lopez 2015). Their results suggest that rising population exposure and greater climate variability play significant roles in explaining the frequency of climate disasters in Asia and the Pacific.

31. 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 variables have been a significant factor in the increase of frequency of intense hydrometeorological disasters in Asia and the Pacific since the 1970s, clearly linking climate change to disaster risks.

32. The evidence is that it is very likely that the rising incidence of GHG emissions in the atmosphere is altering the climate system, and 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 United States are clear indications that both developing and developed countries face climate-related disaster risks.

CHAPTER 3

Comparisons with the Literature

33. Most studies that have tried to link disasters to climate change used climate change models to simulate the likelihood of disasters in particular geographic areas (for example, Cornwall 2016). Others have analyzed particular disasters in specific regions (Stott et al. 2004; Hoerling et al. 2012). Analyzing particular disasters may have the advantage of gaining greater depth to understanding them, but the results using this approach are likely to be affected by selection biases (Heckman et al. 1998) because it is difficult to ascertain their general validity. Similarly, most studies on the effects of climate-related disasters on economic growth focus on particular events or on subsets of disasters in particular regions and times. This obviously raises the question of whether these studies are also affected by selection biases (Albala-Bertrand 1993; Otero and Marti 1995).

34. The statistical–econometric analysis of this paper considers the spectrum of intense climate-related disasters worldwide during 1970–2013 for 184 countries or economies. A distinctive feature of the analysis is that it goes beyond measuring simple correlations between climate change indicators and disasters. Once these correlations are established, we implement cointegration tests to elucidate whether or not such correlations respond to meaningful relationships rather than spurious ones between the number of such disasters and CO_2 accumulation in the atmosphere, and strive to uncover causal effects. We also examine how climate-related disasters and hence how atmospheric carbon accumulation have affected the potential for economic growth using panel country data for the full sample of disasters available for most countries in the world.

35. Two studies related to this paper—Thomas, Albert, and Hepburn (2014) and Thomas and Lopez (2015)—also used multicountry statistical analyses. The former used a sample of 25 Asian countries, but only traced country-specific climatic conditions rather than global climatic trends. Moreover, while the authors found a significant statistical relationship between disasters and local climatic conditions, they did not check for potential biases in their results from the omission of certain variables affecting the likelihood of disasters and local climatic conditions.

36. Thomas and Lopez's study relied on cross-country, time-series statistical analyses to connect disasters and climate change using annual panel data for 153 countries. The study showed a positive impact of global climate change indicators and local ones on hydrometeorological disasters. It also probed whether this connection was meaningful using cointegration analysis. However, since the sample covered only 43-time observations, the time series analysis underlying cointegration was likely weak. Moreover, it did not consider the economic impact of disasters. Neither of these studies considered the effects of disasters on economic growth.

37. The background work for this study is a more solid basis for the conclusions than both of its related studies in two ways: (i) it uses the broadest country sample available of 184 economies across six continents for 43 years; (ii) it uses quarterly instead of annual data, lengthening the longitudinal component of the series to nearly 180 observations and making the cointegration analysis more robust (Appendix 1). Most authors recognize that using a time series analysis with more than 100-time observations is adequate.

38. More broadly, we integrate three major factors affecting the likelihood of the number and impact of natural disasters: global climatic factor (atmospheric CO_2 accumulation); local climate variables (local precipitation and temperature); and socioeconomic variables (per capita gross domestic product, population density). The use of socioeconomic variables is designed to capture vulnerability and exposure of populations to disasters. That we focus on intense disasters—defined as disasters that caused a certain minimum number of deaths or people affected—justifies the need to control for vulnerability and exposure factors. Simultaneously considering the effects of global climatic factors, local climate variables, and socioeconomic variables on disasters is a significant step because the focus is not just one type of factors, such as climate change variables, affecting natural disasters. In looking at various types of factors, we postulate that global climatic changes are likely to affect intense climate-related disasters in addition to local weather events, and that global climatic factors may increase the vulnerability of countries to local weather events. For example, as atmospheric CO_2 accumulates, sea levels tend to increase, making coastal areas much more affected by storms.

39. Finally, we provide first estimates of the impact of the observed increased number of hydrometeorological disasters on economic growth using all available data worldwide instead of focusing only on particular events or regions. Our estimates show that losses of human capital, but not material losses, caused by disasters are the most important factor explaining the estimated negative impact of disasters on economic growth.

CHAPTER 4

Data and Methods

40. In examining the link between climate change and the increase of hydrometeorological incidents and their impact on economic growth, we use sample of 184 economies (para. 37). Specifically, we use quarterly data on disasters—those that cause at least 100 deaths or directly affect at least 1,000 people. The model considers count data of disasters by country i and quarter t for 1970–2013 from the Emergency Events Database (2015). We use two alternative approaches to estimate the impact of global climate change on country disasters (Appendix 2).

41. In Approach I, using the number of natural disasters per country and quarter as the dependent variable, we estimate the effect of global climate indicators as a separate variable directly in the regression analysis, controlling for country-specific effects. The global indicators used are global average temperature and atmospheric CO_2 accumulation. A hypothesis is that global climate variables exert an independent effect on disasters over and above local country conditions. A problem with using the first approach is that the atmospheric CO_2 level may correlate with omitted variables affecting natural disasters, thus biasing the estimates.

42. In Approach II, we estimate two-way fixed effects. First, we control for both country-specific fixed effects and common-to-all-country global effects which vary over time (represented by the coefficients of the time dummy variables). In the second stage, we perform a cointegration analysis between atmospheric CO_2 accumulation and the estimated global time effects obtained from the first stage to test whether these changing global time effects are meaningfully associated with hydrometeorological disasters. Using the cointegration estimates, we calculate the simulated or projected variation in disasters due to current observed rates of increase of CO_2 concentration level with 2010–2013 as the baseline period.

43. In examining the effect of disasters on economic growth, we use a model that controls for both fixed country and unobserved time-varying country-specific effects (Appendix 3). We estimate a regression model in which growth of per capita gross domestic product (GDP) is the dependent variable and our main variable is an approximation of the disaster's impact. We control for lags of per capita GDP growth as well as for fixed effect per country and time-varying country effects. Two different definitions of the variable "disaster" were used in this analysis. First, the direct proportion of the total country population that died due to hydrometeorological disasters (proportion of deaths); second, a generated dummy variable for the disasters that killed more than 100 people or affected at least 1,000 people (hydrometeorological disaster).

44. The final part of the analysis is measuring the impact of CO_2 accumulation in the atmosphere on economic growth (Appendix 3). First, the effect of CO_2 accumulation on the proportion of disaster-induced deaths is calculated using the estimated elasticity of disasters for CO_2 accumulation and the estimated impact of

disasters on deaths as a proportion of total country population. This effect is combined with the elasticity of economic growth for disaster-induced deaths to measure the net elasticity of growth for the atmospheric CO_2 accumulation.

CHAPTER 5

Quantitative Analysis Results

45. In this paper, we present new evidence on the connections between climate change indicators and the increasing number of intense hydrometeorological disasters worldwide. We also explore the impact of disasters on economic growth using a sample of countries or economies which have sufficient data for the analysis.

A. Impacts of Climate Indicators on Country Disasters

46. The estimates explaining the occurrence of intense hydrometeorological disasters show that local- or country-level climate variables are highly significant and have expected signs (Appendix 4). Precipitation deviations exert a positive impact on the number of intense local hydrometeorological disasters, while temperature deviation is negative and significant. Atmospheric CO_2 concentration lagged by 1 year shows a positive and highly significant effect relation showing an additional impact on hydrometeorological disasters.

47. The quantitative results suggest the effect of global climate variables—associated with the atmospheric accumulation of CO_2—on hydrometeorological disasters is positive and significant. And that this exerts an independent effect over and above local climate variables while controlling for exposure and vulnerability of the population. However, it is possible that atmospheric accumulation of CO_2 is correlated with other global variables unrelated to climate change which could also affect the likelihood of disasters in the same direction.

48. We test through a cointegration analysis for the specific effect of the global climate variable. The common-to-all-countries global effects, whether climate-related or otherwise, represented by time, are highly significant and tend to become larger over the time period. In the second stage (cointegration), the estimated time effects and the concentration of atmospheric CO_2 are seen to clearly go together. With this observation, it is highly implausible that hydrometeorological disasters cause the accumulation of carbon in the atmosphere. Hence, it must be the case that the causal direction is from atmospheric carbon accumulation to hydrometeorological disasters.

49. We also calculate the projected variation in disaster due to current observed rates of increase of CO_2 concentration using 2010–2013 as the baseline. The elasticity of hydrometeorological disaster for atmospheric CO_2 level is 33.45.

50. Assuming that CO_2 levels continue increasing at the same rate as in 2010–2013 (2 ppm), the number of intense hydrometeorological disasters per quarter per country

would increase by 0.035 events; that is, the number of disasters would double in 7 years.

51. So it appears that the increase in serious hydrometeorological disasters observed in the 1970–2013 analysis period can be attributed to the continuous worsening of CO_2 accumulations. The effects are very serious as the model attributes about one additional annual major disaster to climate change, which represents about a 4% increase in the number of hydrometeorological disasters per year when we take the simulated impact of CO_2 level.

B. Economic Effects of Disasters

52. An important issue is how intense disasters can affect economic growth. Since quarterly data for per capita GDP growth are not available for all countries we estimate the model using annual data (Appendix 5). This sample contains the same countries or economies used to determine the variables which affect intense hydrometeorological disasters. We use the same period of analysis as in the previous section, between 1970 and 2013.

53. Preliminary analyses show that among all the impacts of hydrometeorological disasters the most important economic consequence is associated with the mortality effects of disasters. Estimates of the effects of the number of intense hydrometeorological disasters on per capita GDP growth (without distinguishing human capital versus physical capital losses) have shown to be not significant. One interpretation is that the likely positive effects of disasters from rebuilding physical capital losses on economic activity when excess productive capacity exists may be offset by the negative effects of the losses of human capital. For this reason we focus on measuring the effects of death caused by disasters on the per capita GDP growth rate of the countries considered.

54. The results suggest that disasters have negative and significant net effects on per capita GDP growth, as measured by the proportion of deaths caused by disasters. However, the relationship between economic growth and deaths may be affected by reverse causality, because it is plausible to assume that economic growth reduces the rate of population death. But even after controlling for deaths not due to disasters the coefficient of the variable proportion of deaths caused by disasters is still negative and highly significant. This supports our hypotheses that causality goes from disaster-induced deaths to economic growth.

55. An important implication of these results is that the effect of deaths due to disasters on economic growth is much larger than the effects of normal mortality. Perhaps disaster-induced deaths tend to be more economically disruptive because they are often more unexpected than other types of deaths.

56. The background work also looked at the impact of the accumulation of CO_2 in the atmosphere on economic growth. We find that a 1% increase in the level of CO_2 accumulated in the atmosphere causes a reduction in the rate of per capita GDP growth for the average or representative country by 0.13%. The results also suggest that if the rate of CO_2 accumulation in the atmosphere continues at the current rate the average rate of economic growth for all countries may be expected to be reduced by 1.5% in 20 years due to the increased climate-related disasters.

CHAPTER 6

Conclusions

57. This paper analyzed the association between climate change variables and the incidence of intense hydrometeorological disasters within a framework that included global and local climate variables as well as socioeconomic factors that aggravate disasters. A key feature of the work is the focus on ascertaining the meaningfulness of the correlations between climate change indicators and disasters. The empirical analysis showed clear nonspurious connections between climate change indicators and the frequency of intense hydrometeorological disasters. Because a causal relationship going from disasters to carbon accumulation in the atmosphere is highly implausible, the finding of a meaningful positive correlation between atmospheric carbon accumulation and natural disasters must suggest a causal relationship going from CO_2 accumulation in the atmosphere to the frequency of disasters.

58. Moreover, we found that the quantitative effect of climate change indicators on the number of intense disasters is large. About one additional major annual disaster in the world can be attributed to the observed annual increases of CO_2 accumulations. This implies that in a business-as-usual scenario in which global climatic indicators continue to deteriorate at recent rates, there would be a 4% annual increase in the number of intense hydrometeorological disasters worldwide attributed to climate change.

59. Finally, there is evidence of a negative impact of intense hydrometeorological disasters on per capita GDP growth. We found a negative and significant impact of disaster-induced human capital losses on per capita GDP growth. We showed that a 1% increase of atmospheric carbon accumulation is associated with a 0.13% fall in the rate of growth of the average or representative country. Moreover, in the business-as-usual scenario, the average rate or per capita economic growth would be reduced by 1.5% in 20 years just as a consequence of increased climate-related disasters. This estimate excludes other factors associated with atmospheric carbon accumulation which may impinge on economic growth.

60. Our findings have implications for development interventions, which we now discuss. For 2016–2017, economists project growth of 3.3% for the global economy and 5.7% for Asia and the Pacific (IMF 2015, ADB 2015). Achieving rates of growth of this order will have great implications for attaining development goals, and for the effectiveness of projects that institutions such as ADB finance. Yet, these growth projections do not integrate climate actions nor the impacts of climate change. The crucial question is whether such growth rates can be sustained using existing patterns of growth without climate action and switching to a low-carbon economy in time.

61. Domestic reforms are paramount to any country's growth prospects, but cross-border factors also matter in our highly globalized world economy. 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.

62. 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 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.

63. 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 and 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.

64. Even so, scientists are cautious about linking any particular disaster to climate change. 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.

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

66. The implication is that while growth must be fast, we need to do this differently. In essence, a new strategy is needed 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.[7]

67. First, disaster resilience needs to be built 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 these events. Returns are also evident even with lesser investments. 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 payoffs from social media alerts, preemptive evacuation, and early warning systems. The Philippines' experience also highlights the benefits of the hazard maps and upgraded rain- and water-level monitoring systems promoted by Project NOAH (Nationwide Operational Assessment of Hazards).

68. 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 $0.40 of every $100 in total international development

[7] http://www.un.org/sustainabledevelopment/sustainable-development-goals/

aid. For governments, one recommended level of spending is 1% to 2% of national budgets. But more important than the exact percentage is promoting the effective use of this spending.

69. Second, policymakers need to raise the priority of urban management as a strategic thrust. Three cities considered most vulnerable to natural hazards are in Asia—Dhaka, Manila, and Jakarta—and all of them are overcrowded and in geographically fragile settings.

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

71. 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. So, adapting to the changing climate through better management of the location decisions of people and businesses, and protecting the natural environment is becoming more urgent.

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

73. Disaster risk management needs to be understood as an investment that goes 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 influential growth scenarios could make a big difference to policy making. And climate mitigation and adaptation need to be seen as a vital and high-return part of this approach.

Appendixes

APPENDIX 1: List of Economies Considered in the Analysis

1	Afghanistan
2	Albania
3	Algeria
4	Angola
5	Antigua and Barbuda
6	Argentina
7	Armenia
8	Australia
9	Austria
10	Azerbaijan
11	Bahamas
12	Bangladesh
13	Barbados
14	Belarus
15	Belguim
16	Belize
17	Benin
18	Bermuda
19	Bhutan
20	Bolivia
21	Bosnia and Herzegovina
22	Botswana
23	Brazil
24	Bulgaria
25	Burkin Faso
26	Cabo Verde
27	Cambodia
28	Cameroon
29	Canada
30	Cayman Islands
31	Central African Republic
32	Chad
33	Chile
34	People’s Republic of China
35	Colombia
36	Comoros
37	Democratic Republic of Congo
38	Republic of Congo
39	Costa Rica
40	Cote d’Ivoire
41	Croatia
42	Cuba
43	Cyprus
44	Czech Republic
45	Denmark
46	Djibouti
47	Dominica
48	Dominican Republic
49	Ecuador
50	Arab Republic of Egypt
51	El Salvador
52	Eritrea
53	Estonia
54	Ethiopia
55	Fiji
56	Finland
57	France
58	Gabon
59	Gambia
60	Georgia
61	Germany
62	Ghana
63	Greece
64	Grenada
65	Guatemala
66	Guinea
67	Guinea-Bissau
68	Guyana
69	Haiti
70	Honduras
71	Hong Kong, China
72	Hungary
73	Iceland
74	India
75	Indonesia
76	Islamic Republic of Iran
77	Iraq
78	Ireland
79	Israel
80	Italy
81	Jamaica
82	Japan
83	Jordan
84	Kazakhstan
85	Kenya
86	Kiribati
87	Republic of Korea
88	Kuwait
89	Kyrgyz Republic
90	Lao People’s Democratic Republic
91	Latvia
92	Lebanon
93	Lesotho
94	Liberia
95	Libya
96	Lithuania
97	Luxembourg
98	Macao, China
99	Macedonia
100	Madagascar

101 Malawi
102 Malaysia
103 Maldives
104 Mali
105 Marshall Islands
106 Mauritiana
107 Mauritius
108 Mexico
109 Federated States of Micronesia
110 Moldova
111 Mongolia
112 Montenegro
113 Morocco
114 Mozambique
115 Myanmar
116 Namibia
117 Nepal
118 Netherlands
119 New Caledonia
120 New Zealand
121 Nicaragua
122 Niger
123 Nigeria
124 Norway
125 Oman
126 Pakistan
127 Palau
128 Panama
129 Papua New Guinea
130 Paraguay
131 Peru
132 Philippines
133 Poland
134 Portugal
135 Puerto Rico
136 Romania
137 Russian Federation
138 Samoa
139 Saudi Arabia
140 Senegal
141 Serbia
142 Seychelles
143 Sierra Leone
144 Slovak Republic
145 Slovenia
146 Solomon Islands
147 Somalia
148 South Africa
149 South Sudan
150 Spain
151 Sri Lanka
152 St. Kitts and Nevis
153 St. Lucia
154 St. Vincent and the Grenadines
155 Sudan
156 Suriname
157 Swaziland
158 Sweden
159 Switzerland
160 Syrian Arab Republic
161 Tajikistan
162 Tanzania
163 Thailand
164 Timor-Leste
165 Togo
166 Tonga
167 Trinidad and Tobago
168 Tunisia
169 Turkey
170 Turkmenistan
171 Tuvalu
172 Uganda
173 Ukraine
174 United Kingdom
175 United States
176 Uruguay
177 Uzbekistan
178 Vanuatu
179 Venezuela
180 Viet Nam
181 Virgin Islands
182 Republic of Yemen
183 Zambia
184 Zimbabwe

APPENDIX 2. Methodology in Estimating the Impacts of Climate Indicators on Country Disasters

1. The dependent variable is the number of intense natural disasters, consisting of nonnegative count values. So, count regression models such as the Poisson or negative binomial need to be used. We use the negative binomial model in equation (1), which unlike the Poisson model, allows for overdispersion between the mean and the variance of the distribution (Johnson, Kotz, and Kemp 1992; Lambert 1992).

2. We estimate equation (1) using quarterly data for 184 countries during 1970–2013, a total of 25,876 observations. Table A2.1 shows the descriptive statistics of the data used.

Table A2.1: Descriptive Statistics of the Data Used, 1970–2013

Variables	Obs.	Mean	Std. Dev.	Minimum	Maximum
Dependent Variable (frequency of intense hydrometeorological disasters)	25,876	0.154	0.569	0.000	15.000
Ln (population density)	25,876	3.808	1.477	0.103	9.980
Ln GDP per capita (constant 2005 US$)	25,876	10.650	2.360	3.988	17.439
Square of Ln GDP per capita	25,876	118.997	53.083	15.904	304.114
Average precipitation deviation	25,876	39.045	37.327	0.073	646.941
Average temperature deviation	25,876	0.743	0.496	0.009	6.539
Population (million)	25,876	34.588	124.261	0.010	1,357.380
CO_2 level	25,876	360.400	20.526	324.090	398.897

CO_2 = carbon dioxide, GDP = gross domestic product, Ln = log, Obs. = observations, Std. Dev. = standard deviation.
Source: Asian Development Bank Independent Evaluation Department.

3. In equation (1) the dependent variable is the annual frequency of intense hydrometeorological disasters, $(\boldsymbol{H_{it}})$. The independent variables are $\boldsymbol{W_{it}}$, the average local precipitation deviation in the country, measured as departures from the average for its 30-year base of 1961–1990 (Schneider et al. 2015); $\boldsymbol{Z_{it}}$, the average local temperature deviation in the country; $\boldsymbol{V_{it}}$, per capita gross domestic product as a proxy for vulnerability to disasters; $\boldsymbol{U_{it}}$, population per country as an indicator of exposure to disasters; and $\boldsymbol{G_t}$, global effects varying at each point of time.[1] We estimate the parameters $\alpha_0, \alpha_1, \alpha_2, \alpha_3, \alpha_4$, and α_5 of the following regression equation:

$$\mathrm{E}[H_{it}|U_{it}, V_{it}, W_{it}, Z_{it}, G_t, v_{it}] = exp(\alpha_0 + \alpha_1 U_{it} + \alpha_2 V_{it} + \alpha_3 W_{it} + \alpha_4 Z_{it} + \alpha_5 G_t) exp(v_{it}), \quad (1)$$

where $\boldsymbol{v_{it}}$ is the stochastic error term. The count of intense disasters—the dependent variable—is characterized by excess zeros. In particular, a high proportion of the quarterly country observations for hydrometeorological disasters have zero counts. Failing to account for the prevalence of zeros in the dependent variable would likely result in inconsistent estimators. For this reason, we use the zero-inflated count model (Johnson, Kotz, and Kemp 1992; Lambert 1992). This model allows elucidating whether the zero-observed dependent variable may either mean a zero probability of having a disaster or a positive probability but no disaster because of random factors (Vuong

[1] Considering only intense disasters (those causing at least 100 deaths or affecting at least 1,000 people) implies that vulnerability and exposure variables need to be considered as explanatory variables.

1989). We estimate the determinants of hydrometeorological disasters using a zero-inflated negative binomial regression model. Vuong tests revealed significant positive test statistics favoring the zero-inflated models over the NB count regression models. Box 1 presents the derivation of this estimator.

Box 1: Derivation of Zero-Inflated Estimator

For each country $\boldsymbol{i}$ and year $\boldsymbol{t}$, there are two possible data generation processes for H_{it} — 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 $g(H_{it}\,|R_{it})$ with probability $1-\rho_i$ generates positive counts from a negative binomial distribution; $R_{it}$is a vector of explanatory variables (in our case $U_{it}, V_{it}, W_{it}, G_t$). In general, we have

$$H_{it} \sim \begin{cases} 0 & with\ probability\ \rho_i \\ g(H_{it}\,|R_{it}\,) & with\ probability\ 1-\rho_i \end{cases}.$$

Then the probability of $\{H_{it} = h_{it}|R_{it}\}$ where h_{it} is a particular value of the variable H_{it}can be expressed as (Johnson, Kotz, and Kemp 1992; Lambert 1992):

$$P(H_{it} = h_{it}|R_{it}, I_{it}) = \begin{cases} \rho(\lambda' I_{it}) + \{1-\rho(\lambda' I_{it})\}g(0|R_{it}) & if\ y_{it} = 0 \\ \{1-\rho(\lambda' I_{it})\}g(h_{it}|R_{it}) & if\ y_{it} > 0 \end{cases}.$$

The probability ρ_i depends on the characteristics (a subset of the explanatory variables) of country i and year t. Hence, ρ_{it} is written as a function of $\lambda' I_{it}$ where I_{it} is the vector of zero-inflated covariates and λ is the vector of zero-inflated coefficients to be estimated.

A probit function using the same explanatory variables as described in equation (1) is specified as the zero-inflated link function—relating the product $\lambda' I_{it}$ (which is scalar) to the probability ρ_{it}. We thus estimate hydrometeorological disasters using a negative binomial zero-inflated regression model. Vuong tests revealed significant positive test statistics which favor the zero-inflated models over the standard negative binomial count regression models. This means that the zero-inflated method is necessary given the preponderance of zeroes of the dependent variable.

This model allows elucidating whether the zero-observed dependent variable either corresponds to countries which in a particular year had a zero probability of having a disaster, or countries that had a positive probability of a disaster but, due to random conditions in that year, experienced no disaster and, consequently, also had a zero dependent variable (Vuong 1989).

4. Two problems that affect common regression analysis particularly concern us. The first is that the series may change together over time on a similar upward trend basis which, as is well-known, implies that any regression analysis between them would yield a positive and significant coefficient without necessarily meaning that they are related (Granger and Newbold 1974). This is the case when the series are not covariance stationary; that is, when the series do not have finite means and autocovariance change over time. The second problem is the relationship between the series may be affected by other variables (often impossible to observe) that are not controlled for in the regression analysis. This is the so-called omitted variable biases.

5. Cointegration allows us to deal with these two problems by enabling us to test whether particular transformations of the series yield covariance stationary processes (and hence can be used to obtain meaningful econometric estimates of the key parameters), and whether the existence of omitted variables is still consistent with obtaining nonspurious correlations over the long run.

6. To implement the analysis of cointegration we estimated coefficients of the quarterly time dummies obtained from the two-way fixed effects model (first stage of the Approach II) are subjected to a cointegration analysis (Engle and Granger 1991) with the quarterly data on atmospheric carbon dioxide (CO_2). We can think of cointegration as describing a particular kind of long-run equilibrium relationship. In particular, we seek to understand whether the estimated coefficients of the time dummies and the global climate variable are positively correlated in a nonspurious way. We use cointegration analysis not as a tool to determine causality but merely as an instrument to confirm the existence of a meaningful or nonspurious correlation between the carbon accumulation in the atmosphere and hydrometeorological disasters. We thus first regress the coefficients of the time dummies (y_t) on the series of atmospheric CO_2 (x_t),

$$y_t = \beta_0 + \beta_1 \cdot x_t + \mu_t, \qquad (2)$$

where β_0 is a fixed coefficient, $\hat{\beta}_1$ is the predicted value of the cointegrating coefficient obtained from the ordinary least squares estimation, and μ_t is the predicted error series. The ordinary least squares estimation of equation (2) gives us an unbiased estimation of $\hat{\beta}_1$. However, its standard error estimate is inconsistent and is not normally distributed. Hence, the usual inferential procedures do not apply.

7. For the significance of β_1—the cointegrating coefficient—it has been shown that both the dependent and independent variables cointegrate if and only if there is an error correction model (ECM) for either y_t and x_t or both (Engle and Granger 1991; Johansen 1988,1995). The ECM involves a particular transformation of equation (2) to allow for a consistent estimation of the cointegrating coefficient. Box 2 shows the derivation of the ECM.

8. The ECM requires the specification of a time process for the stochastic error, μ_t. If μ_t is a stationary of mean zero variable, there exists a stationary autoregressive moving average model for μ_t. We assume an autoregressive model AR(2) for μ_t as follows:

$$\mu_t = \theta_1 \mu_{t-1} + \theta_2 \mu_{t-2} + \varepsilon_t. \qquad (3)$$

In Box 2, we show that equations (2) and (3) imply an autoregressive distributed lag model,

$$y_t = \delta + \theta_1 y_{t-1} + \theta_2 y_{t-2} + \varphi_0 x_t + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \varepsilon_t. \qquad (4)$$

It can be transformed into the following ECM model (Box 2):

$$\Delta y_t = \delta + \lambda_1 \Delta y_{t-1} + k_0 \Delta x_t + k_1 \Delta x_{t-1} + \gamma_1 y_{t-1} + \gamma_2 x_{t-1} + \varepsilon_t, \qquad (5)$$

where $\delta, k_0, k_1, \lambda_1, \gamma_1,$and γ_2 are parameters. From equation (5) the estimator of the cointegrating coefficient is given by the long-run solution

$$\hat{\beta}_1 = -\frac{\hat{\gamma}_2}{\hat{\gamma}_1}. \qquad (6)$$

Box 2: Derivation of Error Correction Model

The model with the time dummies (y_t) and the series of atmospheric carbon dioxide (x_t) can be expressed as

$$y_t = \beta_0 + \beta_1 \cdot x_t + \mu_t, \quad (1)$$

where β_0 and β_1 are the parameters and μ_t is the stochastic error term.

Assume for simplicity that it is an autoregressive model AR(1) (we also tried with AR(2) but, the additional parameters were not significant):

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

In particular, we can estimate equation (2) using ordinary least squares and the unrestricted autoregressive distributed lag (ARDL) model, where the lag lengths are set to eliminate residual autocorrelation, an ARDL(2,2) model. From equations (1) and (2) we have

$$y_t - \beta_0 - \beta_1 \cdot x_t = \mu_t,$$
$$y_{t-1} - \beta_0 - \beta_1 \cdot x_{t-1} = \mu_{t-1}, \text{ and}$$
$$y_{t-2} - \beta_0 - \beta_1 \cdot x_{t-2} = \mu_{t-2}.$$

Using all expressions and equation (2) we have

$$y_t - \beta_0 - \beta_1 \cdot x_t = \theta_1(y_{t-1} - \beta_0 - \beta_1 \cdot x_{t-1}) + \theta_2(y_{t-2} - \beta_0 - \beta_1 \cdot x_{t-2}) + \varepsilon_t ,$$

and rearranging terms

$$y_t = \delta + \theta_1 y_{t-1} + \theta_2 y_{t-2} + \varphi_0 x_t + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \varepsilon_t, \quad (3)$$

where $\delta = (\beta_0 - \theta_1\beta_1 - \theta_2\beta_1), \varphi_0 = \beta_1, \varphi_1 = -\theta_1\beta_1$ and $\varphi_2 = -\theta_2\beta_1$. Equation (3) is an unrestricted autoregressive distributed lag model, ARDL (2,2).

To obtain the error correction model form we used the next two equalities (developing right sides of both equalities directly reached the left sides):

$$y_t - \theta_1 y_{t-1} - \theta_2 y_{t-2} = \Delta y_t + \theta_2 y_{t-1} - (\theta_1 + \theta_2 - 1) y_{t-1} \text{ and}$$
$$\varphi_0 x_t + \varphi_1 x_{t-1} + \varphi_2 x_{t-2} = \varphi_0 \Delta x_t - \varphi_2 \Delta x_{t-1} + (\varphi_0 + \varphi_1 + \varphi_2) x_{t-1},$$

where $\Delta y_t = y_t - y_{t-1}$, $\Delta x_t = x_t - x_{t-1}$. Using both equalities in equation (3) and rearranging terms:

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

$$\Delta y_t = \delta + \lambda_1 \Delta y_{t-1} + k_0 \Delta x_t + k_1 \Delta x_{t-1} + \gamma_1 y_{t-1} + \gamma_2 x_{t-1} + \varepsilon_t, \quad (4)$$

where $\lambda_1 = -\theta_2, k_0 = \varphi_0, k_1 = -\varphi_1, \gamma_1 = \theta_1 + \theta_2 - 1$ and $\gamma_2 = \varphi_0 + \varphi_1 + \varphi_2$. We estimate equation (4) using the ordinary least squares method. From equation (4) the estimator of the cointegrated coefficient is given by the long-run solution

$$\hat{\beta}_1^{\,*} = -\frac{\hat{\gamma}_2}{\hat{\gamma}_1}. \quad (5)$$

9. Thus, using the estimated coefficients $\hat{\gamma}_1$ and $\hat{\gamma}_2$ and their respective standard errors we can obtain a consistent measure for $\hat{\beta}_1^{\,*}$ and its correct standard error to analyze its significance. Another test to verify cointegration is the maximum-likelihood method developed by Johansen (1988, 1995) of vector error correction modeling (Box 3).

Box 3: Vector Error Correction Model and Johansen Test

In a bivariate model with y_t and x_t variables, there exists a β_0, β_1 such that $y_t - \beta_0 - x_t\beta_1 = \mu_t$ is $I(0)$ even though x_t and y_t may be nonstationary series. This means the two variables are cointegrated or have a stationary long-run relationship even though individually they are nonstationary series.

A vector autoregression model with l lags can be represented as

$$z_t = \rho_1 z_{t-1} + \rho_1 z_{t-1} + \cdots + \rho_1 z_{t-1} + \varphi\tau_t + \varepsilon_t\ , \qquad (1)$$

where $z_t = \binom{y_t}{x_t}$ is an $2x1$ vector of $I(1)$ variables, τ_t is a vector of deterministic variable and ε_t is a $2x1$ vector of identically and normally distributed errors with mean zero and nondiagonal covariance matrix Σ. Given that the variables are cointegrated, equation (1) can be represented by the following equilibrium correction model (equation 2):

$$\Delta z_t = \eta\omega' z_{t-1} + \textstyle\sum_{i=1}^{l-1} \Gamma_i\, \Delta z_{t-1} + \delta \cdot t + v + \varepsilon_t. \qquad (2)$$

Vectors η and ω are the key coefficients. ω is an $2xr$ matrix of cointegrating vectors that explains the long-run relationship of the variables. η is also an $2xr$ matrix that explains long-run disequilibrium of the variables. v and t are the deterministic trend component. It is important to note that for cointegration to exist, matrices η and ω should have reduced rank r, where $r < 2$. The identification of the cointegrating vector uses maximum likelihood method developed by Johansen (1988, 1995).

10. For the problem of omitted variables, it has been shown that if cointegration tests are passed it means that—regardless of the possible existence of omitted variables—the estimated cointegrating coefficient from equation (6) is unbiased and consistent (Pashourtidou 2003). Although the adjustment coefficients (short-run estimates) may be biased, our focus is on the long-run correlation between the variables of interest. In fact, what we seek to discover is precisely how a continuous accumulation of CO_2 in the atmosphere (a long-run effect) may be associated with the increase of natural disasters over the long run.

APPENDIX 3: Methodology in Measuring the Economic Effects of Disasters

1. Finding an effect of disasters on economic growth has been difficult. The World Bank and United Nations (2010) did a literature review of natural disasters and their growth effects, but did not find a consistent conclusion. The main reason for this is the potential effect of omitted variables that may affect both gross domestic product (GDP) growth and natural disasters. No matter how many control variables are used, one is never sure that there might not be other relevant unobserved omitted variables.

2. Several studies, however, do find a negative effect on GDP growth (Otero and Marti 1995; Benson 1997; Benson and Clay 1998; Murlidharan and Sha 2001; Hochrainer 2009; Cuaresma 2009). They show the impact depends on the size of the disaster, the size of the economy, and economic conditions. However, Albala-Bertrand (1993) found no significant long-term effect in developed countries, and in developing countries the author reports a negative effect that tends to disappear after 2 years. Caselli and Malhotra (2004) argue that disasters do not reduce GDP growth.

3. Loayza et al. (2009) estimate the medium-term effects on economic growth of different natural hazards using a model with three main sectors (agriculture, industry, services) and the whole economy. Their main conclusion is that economic growth is generally lower after a disaster; however, the effect depends on the type of natural hazard and it is not always statistically significant. Fomby, Ikeda, and Loayza (2009) find that moderate and severe disasters affect growth more in poor countries than in rich ones.

4. Disasters have differential impacts on various assets. They affect human capital mainly through deaths and injuries, and nonhuman capital from losses of infrastructure, livestock, and productive capital. We hypothesize that these two types of assets affected by disasters entail fundamentally different effects on economic growth. While the losses of human capital hurt economic growth in a fundamental way, the losses of nonhuman capital can be recovered quite rapidly.

5. The process of rebuilding physical capital often entails greater demand for domestic industries. If there is excess industrial capacity, this increased demand may allow for a greater use of the production capacity.[1] Thus, paradoxically rebuilding physical capital losses may induce greater industrial production and a faster rate of economic growth. Regressing growth on disasters without separating their effects on these two types of assets would likely give weak and ambiguous correlations. However, if we focus on the human capital consequences, we are likely to obtain stronger links. We show this by first using the standard approach of estimating the effects of disasters without separating the effects, finding no statistically significant effects of disasters on growth. But focusing on the human losses caused by disasters gives negative and statistically significant effects.

[1] In most cases, natural disasters affect only part of a country´s territory, rarely all of it. This means that industries located in unaffected areas can expand production quite rapidly to satisfy the demands for material goods from affected areas. Moreover, if the marginal costs of production do not increase too rapidly with production levels (as may be expected when there is unused capacity), one can expect that the increased supply of goods will result in only small price increases.

6. An additional contribution to the literature of our analysis is the use of a new model that controls for both fixed country and unobserved time-varying country-specific effects (TVCE), as developed and first applied by López and Palacios (2014). The idea is that many potentially omitted factors affecting the impact of disasters may be captured by TVCE. That is, while previous studies control for country fixed effects and common-to-all countries time effects, they fail to control for TVCE. We hope that using TVCE considerably mitigates the potential biases due to omitted variables that may affect each country over time in a changing manner.

7. We estimate a model in which per capita GDP growth is the dependent variable and our main variable is an approximation of a disaster's impact. We control for lags of GDP growth as well as for fixed effect per country and time-varying country effects. The TVCE method is a parsimonious approach aimed at controlling for country-specific variables that are either unobserved or difficult to measure; these may change over time and are specific to each country. The TVCE approach is a generalization of both the standard fixed-effects model and the country-specific time trends approach.

8. Taking into consideration the length of our data base, we control for 5-year country-specific variable effects. In other words, we have a different dummy variable for each country for every 5-year period. The following equation shows the estimating equation. In this case $\alpha_{i,j}$ represents how previous per capita GDP growth affects the current level, while β_{i,t^*} is the parameter which estimates the TVCE. $\theta_{i,t-j}$ is our parameter of interest relating disasters to per capita GDP growth. Moreover, ε_i is the fixed country effect and $\mu_{i,t}$ is the error of the estimation.

$$GdpGrowth_{i,t} = \sum_{j=1}^{n} \alpha_{i,j} \cdot GdpGrowth_{i,t-j} + \sum_{j=0}^{m} \theta_{i,t-j} \cdot Disaster_{i,t-j} + \sum_{t^*=\{t:t+5\}}^{T-5} \beta_{i,t^*} \cdot v_{i,t^*} + \varepsilon_i + \mu_{i,t}\,.$$

9. We use two different definitions of the variable "disaster." First, we use directly the proportion of the total country population that died due to hydrometeorological disasters. This variable is named "proportion of deaths." Second, we generate a dummy variable for the disasters that killed more than 100 people or affected at least 1,000 people. We called this variable "hydrometeorological disaster."

APPENDIX 4: Impacts of Climate Indicators on Country Disasters

1. The first column in Table A4.1 shows the estimates using one-way fixed effects (Approach I), using carbon dioxide (CO_2) accumulation as an indicator of global climate effect. The second column shows the estimates of the two-way fixed effects (first stage of Approach II) using quarterly time dummies in addition to country effects (Table A4.2). The Voung test rejects the hypothesis that negative binomial zero-inflated estimators are equal to the negative binomial estimators at 1% level of significance. Therefore, there is evidence that the zero-inflated negative binomial model is needed to avoid inconsistent estimators.

Table A4.1: Determinants of Intense Hydrometeorological Disasters

	NBZI	
Item	One-way fixed effects (1)	Two-way fixed effects (2)
Ln population density	0.151***	0.112**
	[0.0361]	[0.0330]
Ln GDP pc	0.148**	0.183***
	[0.0751]	[0.0700]
Squared Ln GDP pc	(0.00678)**	(0.00850)***
	[0.00314]	[0.00290]
Precipitation deviation	0.000497	0.0050***
	[0.000587]	[0.001160]
Temperature deviation	(0.6820)***	(0.4941)***
	[0.0817]	[0.0798]
Population (million)	0.00155***	0.00150***
	[0.0000953]	[0.0000800]
CO_2 atmospheric level (1-year lag)	0.0175***	
	[0.00109]	
Observations	25,876	25,876
Akaike information criterion	17,833.27	17,603.71
Bayesian information criterion	18,135.23	19,325.70
Likelihood ratio test	56.85***	77.26*
Vuong test	15.69***	14.98*

( ) = negative, CO_2 = carbon dioxide, GDP = gross domestic product, Ln = log, NBZI = negative binomial zero-inflated, pc = per capita.
Note: Standard errors in brackets. * significant at 10%, ** significant at 5%, *** significant at 1%.
Source: Asian Development Bank Independent Evaluation Department..

2. Precipitation deviation, the key feature of floods and storms, has a positive and significant association with the incidence of local hydrometeorological disasters. Local temperature deviation is negative and significant. Atmospheric CO_2 concentration lagged by 1 year shows a positive and highly significant relation showing an additional impact on hydrometeorological disasters. Thus, the global effects associated with the atmospheric accumulation of CO_2 appear to exert an independent effect over and above local climatic events. This makes sense as global climatic factors may increase the vulnerability of countries to local weather events. For example, as atmospheric CO_2 accumulates, sea levels tend to increase, making coastal areas much more affected by storms.

3. It is possible that global climate variables used in Approach I (first column of Table A4.1) are correlated with other global variables unrelated to climate change impacting the likelihood of disasters in the same direction. This would then imply that the coefficient the CO_2 variable may be inconsistent. That is why we use Approach II, which in its second stage uses cointegration to test for specific effects of the global climate variable.

4. The second column of Table A4.1 reports the first stage of Approach II. The common-to-all countries time effect represented by the coefficients of the quarterly time dummy variables captures any global effects. The time dummy coefficients (Table A4.2) are highly significant and become larger over the time period. In the second stage, we implement cointegration analysis between the estimated time dummy coefficients and the atmospheric CO_2.

5. The first column of Table A4.3 provides the ordinary least squares estimates of regressing the coefficients of the time dummy variables with CO_2 atmospheric concentration. The coefficients are not distributed asymptotically normal due to the lack of stationarity of the series, so that the usual t-statistics do not apply. But we can use the estimated coefficients to test if the predicted errors are stationary. Even if all individual series are nonstationary, the linear combination of nonstationary series could be stationary.

6. Table A4.3 shows the results of the tests for stationarity or cointegration using the series of predicted errors. Since the time series is quite short, we use an unrestricted autoregressive distributed lag model, which has shown to be appropriate for time series between 100 and 500 observations (Box and Tiao 1975; Simonton 1977). Both the Dickey-Fuller and Dickey-Fuller generalized least squares test whether a unit root is present in the series of the predicted errors. Tabulated critical values at 1% and 5% are more exigent than usual t-test (MacKinnon 1994, 2010; Elliott, Rothenberg, and Stock 1996). The Dickey-Fuller and the Dickey-Fuller generalized least squares statistics allow rejection of the null hypothesis that the series have a unit root. The time dummy coefficients and the global variables are integrated of order one (that is, the predicted error is stationary), suggesting that the series cointegrate.

Table A4.2: Estimated Coefficients of the Time Dummy Variables (Approach II, Stage I)

Time	Coefficient	Time	Coefficient	Time	Coefficient	Time	Coefficient	Time	Coefficient
1970q1		1979q1	0.558	1988q1	0.509	1997q1	0.782	2006q1	1.842
1970q2	0.174	1979q2	1.000	1988q2	1.112	1997q2	1.139	2006q2	2.093
1970q3	1.168	1979q3	0.849	1988q3	1.815	1997q3	1.473	2006q3	2.280
1970q4	1.179	1979q4	1.021	1988q4	1.116	1997q4	1.062	2006q4	1.671
1971q1	0.233	1980q1	0.770	1989q1	(0.432)	1998q1	1.523	2007q1	1.710
1971q2	0.588	1980q2	0.543	1989q2	1.218	1998q2	1.343	2007q2	1.595
1971q3	0.443	1980q3	1.360	1989q3	1.314	1998q3	1.927	2007q3	2.474
1971q4	(0.133)	1980q4	0.393	1989q4	0.535	1998q4	1.551	2007q4	2.080
1972q1	(0.453)	1981q1	0.728	1990q1	0.488	1999q1	1.334	2008q1	1.747
1972q2	0.788	1981q2	0.620	1990q2	1.306	1999q2	1.424	2008q2	1.314
1972q3	0.200	1981q3	1.202	1990q3	1.236	1999q3	2.169	2008q3	2.312
1972q4	(0.143)	1981q4	1.418	1990q4	0.822	1999q4	1.819	2008q4	2.056
1973q1	0.411	1982q1	0.949	1991q1	0.758	2000q1	1.434	2009q1	1.716
1973q2	0.145	1982q2	1.017	1991q2	0.578	2000q2	1.776	2009q2	1.326
1973q3	0.010	1982q3	1.186	1991q3	1.633	2000q3	2.010	2009q3	2.121
1973q4	1.079	1982q4	1.018	1991q4	0.528	2000q4	1.654	2009q4	1.906
1974q1	0.932	1983q1	0.597	1992q1	1.080	2001q1	1.309	2010q1	1.770
1974q2	0.290	1983q2	0.890	1992q2	1.102	2001q2	1.917	2010q2	1.960
1974q3	0.997	1983q3	1.362	1992q3	1.410	2001q3	2.263	2010q3	2.118
1974q4	0.603	1983q4	1.145	1992q4	0.920	2001q4	1.627	2010q4	1.754
1975q1	0.204	1984q1	0.708	1993q1	1.756	2002q1	1.537	2011q1	0.757
1975q2	0.234	1984q2	1.027	1993q2	1.614	2002q2	1.731	2011q2	0.886
1975q3	(0.027)	1984q3	0.972	1993q3	1.707	2002q3	2.178	2011q3	1.093
1975q4	(0.653)	1984q4	1.149	1993q4	1.591	2002q4	1.604	2011q4	1.032
1976q1	(0.528)	1985q1	1.236	1994q1	0.896	2003q1	1.690	2012q1	1.041
1976q2	0.262	1985q2	1.250	1994q2	1.374	2003q2	1.453	2012q2	1.021
1976q3	0.330	1985q3	1.041	1994q3	1.582	2003q3	1.829	2012q3	1.062
1976q4	0.802	1985q4	1.356	1994q4	1.361	2003q4	1.470	2012q4	0.897
1977q1	0.671	1986q1	0.740	1995q1	1.156	2004q1	1.609	2013q1	1.361
1977q2	0.740	1986q2	1.042	1995q2	1.664	2004q2	1.808	2013q2	0.788
1977q3	1.528	1986q3	1.339	1995q3	1.984	2004q3	1.983	2013q3	1.172
1977q4	0.576	1986q4	0.805	1995q4	1.763	2004q4	1.518	2013q4	0.755
1978q1	0.964	1987q1	0.952	1996q1	1.128	2005q1	1.847		
1978q2	0.945	1987q2	0.008	1996q2	1.069	2005q2	1.843		
1978q3	1.383	1987q3	1.328	1996q3	1.838	2005q3	2.380		
1978q4	1.104	1987q4	1.140	1996q4	1.413	2005q4	1.860		

( ) = negative, q = quarter
Notes: * significant at 10%, ** significant at 5%, *** significant at 1%.
Source: Asian Development Bank Independent Evaluation Department.

Table A4.3: Cointegration Estimates of Hydrometeorological Disasters–CO_2 Series

Item	Level [a]	First Diff. (D.1) [b] (ECM)
CO_2 (t)	0.0184	
	[0.0021]	
D.1 Time dummy coefficients (t-1) $(\hat{\lambda}_1)$		(0.2320)***
		[0.0789]
D.1 CO_2 (t-1) $(\hat{k}_1)$		(0.0654)***
		[0.0109]
D.2 CO_2 (t-1) $(\hat{k}_1)$		0.0464***
		[0.0114]
Time dummy coefficients (t-1) $(\hat{\gamma}_1)$		(0.3480)***
		[0.0852]
CO_2 (t-1) $(\hat{\gamma}_2)$		0.00628***
		[0.00216]
Constant	(5.424)***	(1.827)**
	[0.746]	[0.703]
Observations	175	173
Akaike information criterion	242.8	151.3
Bayesian information criterion	249.1	170.2
Tests for Stationarity		
Dickey-Fuller	(2.662)*	
Dickey-Fuller generalized least squares	(2.071)**	

( ) = negative, CO_2 = carbon dioxide, ECM = error correction model.
Note: Standard errors in brackets.

See Appendix 2, equation (2), See Appendix 2, equation (5).
* significant at 10%, ** significant at 5%, significant at 1%.
Source: Asian Development Bank Independent Evaluation Department.

7. In addition to the tests reported in the first column of Table A4.3, we also implemented a more powerful cointegration test developed by Johansen (1995) presented in Table A4.4. This test estimates a vector error correction model between hydrometeorological disasters and CO_2 concentrations in the atmosphere. The Johansen test also shows clear evidence of cointegration between the series.

Table A4.4: Johansen Test for Cointegration

Rank *r*	Johansen Test	Critical Value 1%
0	27,47***	16,31
1	5,70	6,51

Note: * significant at 10%, ** significant at 5%, *** significant at 1%.
Source: Asian Development Bank Independent Evaluation Department.

8. These tests all conclude that the two series cointegrate. However, these tests are not generally considered to have sufficient power when the sample size for each series is relatively small. When samples are small the literature recommends the use of autoregressive distributed lags to obtain a more reliable test for cointegration (Pesaran, Shin, and Smith 2001). Thus, we corroborate the existence of stationarity and cointegration using an error correction model, as shown in equation (5) of Appendix 2,

implemented using an autoregressive distributed lag. The second column in Table A4.3 shows the estimates of the error correction model using an autoregressive distributed lag for the series. The coefficient of CO_2 (t-1) $(\hat{\gamma}_2)$is positive and significant, and the error correction coefficient, associated with the time dummy coefficients (t-1) $(\hat{\gamma}_1)$, is negative and significant. The statistical significance of these two coefficients implies there may be a nonspurious correlation between the series. Moreover, the adjustment process is stable due to the fact that $|\hat{\gamma}_1| < 1$.

9. The estimates of the γ_1 and γ_2 coefficients allow us to obtain a measure of the key coefficient $\hat{\beta}_1^*$ by using equation (6) in Appendix 2. Most importantly, this estimate of $\hat{\beta}_1^*$ is unbiased and distributes according to a normal distribution; this allows us to obtain consistent statistical inference. From the standard errors and covariances of γ_1 and γ_2 coefficients, we derive the standard error of $\hat{\beta}_1^*$using the Delta method (Oehlert 1992). Table A4.5 shows the estimated value of $\hat{\beta}_1^* = 0.0180$ with its standard error thus estimated equal to 0.0042. That is, the cointegrating coefficient is in fact positive and statistically significant at a 1% level of significance.

Table A4.5: Cointegration—Hydrometeorological Disasters–CO_2 Level

Item	Estimated coefficients of the time dummy variables	
	Short run	Long run
CO_2 level	0.0184	0.0180***
	[0.0021]	[0.0042]

CO_2 = carbon dioxide.
Note: Standard errors in brackets.
* significant at 10%, ** significant at 5%, *** significant at 1%.
Source: Asian Development Bank Independent Evaluation Department.

10. Table A4.5 shows the short- and long-run estimates of $\hat{\beta}_1$ for hydrometeorological disasters. The long-run coefficient is statistically significant at 1% and is quite similar to the short-run coefficient. Using the $\hat{\beta}_1$, we calculate the elasticity of time dummy coefficients with respect to the CO_2 level (Table A4.6).

Table A4.6: Time Dummy Coefficients and CO_2 Level

Item	CO_2 Level
Marginal effect $(\hat{\beta})$	0.0180
Average sample value of CO_2 level (1970–2013)	360.4
Average value of time dummy coefficients (1970–2013)	1.16
Elasticity of time dummy coefficients for CO_2 level	5.6

CO_2 = carbon dioxide.
Source: Asian Development Bank Independent Evaluation Department.

11. Next, we calculate the simulated variation in disasters due to current observed rates of increase of CO_2 concentration level using 2010–2013 as the baseline (Table A4.7). Thus, if atmospheric CO_2 levels continue increasing at the same rate as in this period, the number of intense hydrometeorological disasters per quarter per country would increase by 0.035 events; that is, the number of disasters would double in 7 years.

Table A4.7: CO_2 Concentration and Hydrometeorological Disasters: Simulated Variation, 2010–2013

Item	CO_2 Level
For Simulation	
CO_2 stock (ppm)	395
Average disaster occurrence per year	0.212
Average value of time dummy coefficients	1.216
Current Annual Increase CO_2 stock (ppm)	2.0
Simulated variation in quarterly disasters due to current rate of increases in global variables	0.035

CO_2 = carbon dioxide, ppm = parts per million.
Source: Asian Development Bank Independent Evaluation Department.

12. Cointegration may show the existence of meaningful correlations but not necessarily of causality. If a meaningful correlation between the series exists then our approach to ascertaining causality relies on the observation that if two variables exhibit a nonspurious correlation there must be at least one direction of causality between them (Asteriou and Hall 2011; Granger 1988). The next step, therefore, is to establish whether prior reasoning and scientific knowledge may allow us to discard one of the directions of causality. If so, we can conclude without further statistical tests which is the causal relation associated with the existence of a nonspurious correlation between the two series. This is the approach that we use here. This observation leads us to the following conclusion: it is highly implausible that hydrometeorological disasters cause the accumulation of carbon in the atmosphere (of course, in the case of other disasters such as volcanic eruptions this may not be true). Hence, it must be the case that the causal direction is from atmospheric carbon accumulation to hydrometeorological disasters.

13. To test causality in the long run, we follow Clive and Lin 1995. Using equation (2) in Box 3 in Appendix 2 and defining $z_t = \binom{y_t}{x_t}$, we estimate that the best model for our variables is which has five lags (i.e., $l = 5$). Thus,

$$\Delta z_t = \eta \omega' z_{t-5} + \sum_{i=1}^{4} \Gamma_i \, \Delta z_{t-1} + \delta \cdot t + v + \varepsilon_t.$$

14. We verified if the coefficients of $\{\Gamma_i\}_{i=1}^{4}$ for each element of y_t are jointly different from zero. If this fact can be rejected it will give us evidence of causality in the long run. Table A4.8 shows the results. When the causality from CO_2 to coefficient of dummy time variables is tested, it is possible to reject the null hypothesis at 1%. When the causality from coefficient of dummy time variables to CO_2 is tested, it is not possible to reject the null hypothesis. Therefore, we conclude that the direction of causality must go from atmospheric CO_2 accumulation to hydrometeorological disasters.

Table A4.8: Test of Granger Causality in the Long Run

	y_t	x_t
Hypothesis	CO_2→Coefficient of time dummy variables	Coefficient of time dummy variables→ CO_2
H_0	$\Gamma_1 = 0$ $\Gamma_2 = 0$ $\Gamma_3 = 0$ $\Gamma_4 = 0$	$\Gamma_1 = 0$ $\Gamma_2 = 0$ $\Gamma_3 = 0$ $\Gamma_4 = 0$
F-test	33.68***	2.43
p-value	0.000	0.6578

CO_2 = carbon dioxide.
Note: * significant at 10%, ** significant at 5%, *** significant at 1%.
Source: Asian Development Bank Independent Evaluation Department.

APPENDIX 5. Economic Effects of Disasters

1. We estimate the model using annual data as no quarterly data for gross domestic product (GDP) are available. This sample contains the same countries that we used to determine the variables which affect intense hydrometeorological disasters (Appendix 1). Table A5.1 shows the main statistics for the 184 countries included in the analysis.

Table A5.1: Descriptive Statistics—184 Countries with an Intense Hydrometeorological Disaster

Variable	Mean	Std. Dev.	Min.	Max.	Observations
Hydro disaster dummy	0.629	1.626	0	28.00	6,754
Proportion of deaths (one per 10,000 people)	0.0327	0.521	0	26.52	6,754
GDP per capita Growth (%)	3.587	6.116	(64.04)	106.2	6,754

( ) = negative, GDP = gross domestic product, Std. Dev. = standard deviation.
Source: Asian Development Bank Independent Evaluation Department.

Table A5.2: Per Capita GDP Growth and Number of Hydrometeorological Disasters

Item	(1)	(2)	(3)
L. Per capita GDP growth	0.0638***	0.0640***	0.0640***
	[0.0135]	[0.0135]	[0.0135]
L2. Per capita GDP growth	(0.000217)	(0.000203)	(0.000117)
	[0.0129]	[0.0129]	[0.0129]
L.Ln GDP pc	(28.06)***	(28.08)***	(28.11)***
	[1.023]	[1.023]	[1.024]
L. N° Hydro disasters	(0.0847)	(0.0830)	(0.0755)
	[0.0814]	[0.0814]	[0.0819]
L2. N° Hydro disasters		0.0904	0.0918
		[0.0816]	[0.0816]
L3. N° Hydro disasters			0.0691
			[0.0848]
L. Proportion of deaths unrelated to disaster	(0.0653)***	(0.0647)***	(0.0645)***
	[0.0170]	[0.0170]	[0.0170]
Net effect	(0.0847)	0.0073	0.0850
	[0.0814]	[0.1163]	[0.1506]
Observations	6,669	6,669	6,668
Akaike Information Criterion	41,164.53	41,162.36	41,154.34
Bayesian Information Criterion	49,378.44	49,383.07	49,381.67

( ) = negative, GDP = gross domestic product, L = lag operator (1-year lag).
Note: Time-varying country-specific effect estimation controls for 5-year variable effects. Standard errors are in brackets.
* = significant at 10%, ** = significant at 5%, *** = significant at 1%.
Source: Asian Development Bank Independent Evaluation Department.

2. Table A5.2 shows the time-varying country-specific effect estimates of the effects of the number of intense hydrometeorological disasters on per capita GDP growth without distinguishing human capital versus physical capital losses. As can be seen, there are no significant parameters. One interpretation is that the likely positive effects of disasters due to the rebuilding of physical capital losses on economic activity when excess productive capacity exists may be offset by the negative effects of the loss of human capital.

3. That is why here we focus exclusively on the human capital losses caused by disasters (Table A5.3). In particular, we use the number of deaths induced by disasters as a proportion of a country's total population, instead of merely the number of disasters as the key explanatory variable. In sharp contrast with the results in Table A5.2, using the proportion of deaths over the total population caused by disasters, the effects of the first, second, and third lags of this variable on per capita GDP growth are all negative and almost all of them are statistically significant. The net effect of the three lags is also negative and significant.

Table A5.3: Per Capita GDP Growth and Proportion of Deaths Due to Disasters

Item	(1)	(2)	(3)
L. Per capita GDP growth	0.0639***	0.0634***	0.0632***
	[0.0135]	[0.0135]	[0.0135]
L2. Per capita GDP growth	(0.0000917)	0.0002190	0.0002020
	[0.0129]	[0.0129]	[0.0129]
L. Ln GDP pc	(28.03)***	(28.07)***	(28.06)***
	[1.023]	[1.023]	[1.023]
L. Proportion of deaths due to disaster	(0.195)	(0.226)*	(0.248)*
	[0.135]	[0.136]	[0.136]
L2. Proportion of deaths due to disaster		(0.238)*	(0.273)**
		[0.131]	[0.132]
L3. Proportion of deaths due to disaster			(0.189)**
			[0.0932]
L. Proportion of deaths unrelated to disaster	(0.0651)***	(0.0686)***	(0.0681)***
	[0.0170]	[0.0171]	[0.0171]
Net effect of disaster-induced deaths	(0.195)	(0.464)***	(0.709)***
	[0.135]	[0.200]	[0.233]
Observations	6,669	6,669	6,668
Akaike Information Criterion	41,164.53	41,162.36	41,154.34
Bayesian Information Criterion	49,378.44	49,383.07	49,381.67

( ) =negative, GDP = gross domestic product, L = lag operator (1-year lag).
Notes: TVCE controls for 5-year variable country-specific effects. Standard errors are in brackets.
* = significant at 10%, ** = significant at 5%, *** = significant at 1%.
Source: Asian Development Bank Independent Evaluation Department.

4. However, the relationship between economic growth and deaths may be affected by reverse causality, because it is plausible to assume that economic growth reduces the rate of population death. To mitigate this problem, we also control for the proportion of deaths (over the total population) not due to disasters, finding a negative relationship as expected. The key issue is that even after controlling for deaths not due to disasters, the coefficient of the variable proportion of deaths caused by disasters is still negative and highly significant. Moreover, there is an extremely low correlation of deaths caused by disasters and deaths due to other factors (correlation coefficient 0.002), which reinforces our hypotheses that causality goes from the proportion of disaster-induced deaths to economic growth and not the other way around. In addition, the regression in Table A5.3 also controls for country per capita income to reflect that per capita income and economic growth may be (negatively) correlated

5. An important implication of the results is that the effect of deaths due to disasters on economic growth is much larger than the effects of normal mortality. This may reflect the fact that disaster-induced deaths are more traumatic, especially because they often involve a greater proportion of younger people at their peak productive age. Also, disaster-induced deaths tend to be more economically disruptive because they are often more unexpected than normal deaths.

6. Using the coefficient equal to –0.709 obtained when we use three lagged effects as reported in the last column of Table A5.3, we obtain that a 1% increase of disaster-induced deaths is likely to cause the growth rate of the representative country to decline by 0.0064% over the first 3 years after the disaster. Also, it appears that the negative effect of disaster deaths on economic growth tends to persist for at least 3 years.

7. This analysis closes by measuring the impact of the accumulation of carbon dioxide (CO_2) in the atmosphere on economic growth. We start by using the elasticity of disasters for CO_2 accumulation as reported earlier. Next, we estimate the impact of disasters on deaths as a proportion of the total country population. Using this measure and the elasticity of disasters, we can estimate the effect of CO_2 accumulation on the proportion of disaster-induced deaths. Finally, we combine this last effect with the elasticity of economic growth for disaster-induced deaths to measure the net elasticity of growth for atmospheric CO_2 accumulation. That is, we use the following expression to estimate the net effect of CO_2 accumulation on economic growth:

$$\xi_{GdpGrowth,CO_2} = \xi_{GdpGrowth,Proportion\ of\ deaths} \cdot \xi_{Proportion\ of\ deaths,Disasters} \cdot \xi_{Disasters,CO_2},$$

where $\xi_{GdpGrowth,CO_2}$, $\xi_{GdpGrowth,Proportion\ of\ deaths}$, $\xi_{Proportion\ of\ deaths,Disasters}$ and $\xi_{Disasters,CO_2}$

represent the elasticities of growth for CO_2 accumulation, growth for the proportion of deaths, proportion of deaths for the number of disasters, and number of disasters for CO_2 accumulation, respectively.

8. Table A5.4 shows details of this exercise. We find that a 1% increase in the level of CO_2 accumulated in the atmosphere causes a reduction of the rate of GDP growth for the average or representative country by 0.13%. This figure may seem small given that atmospheric CO_2 is increasing by only 0.5% per year. However, we note that this effect applies to the average of all countries whether they are affected by a disaster or not. Moreover, if the rate of carbon accumulation in the atmosphere continues at the current rate, one may expect that the average rate of economic growth for all countries may be reduced by 1.5% in 20 years due to the increased climate-related disasters.

Table A5.4: Elasticity of Per Capita GDP Growth for CO_2

Item	Representative Country	Countries with at least one disaster (2004–2013)
$\xi_{Disasters,CO_2}$	33.45	33.45
$\xi_{Proportion\ of\ deaths,Disasters}$	0.6	0.6
$\xi_{GdpGrowth,Proportion\ of\ deaths}$	(0.0066)	(0.0073)
$\xi_{GdpGrowth,CO_2}$	(0.13)	(0.15)

( ) = negative, GDP = gross domestic product.
Source: Asian Development Bank Independent Evaluation Department.

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