AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
<http://ageconsearch.umn.edu>
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

Disaster Risk, Social Vulnerability and Economic Development

Patrick S. Ward

Department of Agricultural Economics, Purdue University

Gerald E. Shively

Department of Agricultural Economics, Purdue University
Purdue Climate Change Research Center

May 2, 2011

*Selected Paper prepared for presentation at the Agricultural & Applied Economics Association
2011 AAEA & NAREEA Joint Annual Meeting, Pittsburgh, Pennsylvania, July 24-26, 2011*

© 2011 by Patrick Ward and Gerald Shively. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

Disaster Risk, Social Vulnerability and Economic Development*

Patrick Ward[†]
Gerald Shively[‡]

May 2, 2011

Abstract

We examine the extent to which economic development reduces both a country's disaster risk and its social vulnerability to climate-related disasters. Global climate change is expected to increase the frequency and intensity of extreme weather events, such as droughts, floods, and various types of storms. Moreover, the effects of these extreme weather events are expected to be borne disproportionately in areas of the world already challenged by underdevelopment. We find that the ability of economic development to reduce disaster risk depends on a country's income level; additional income becomes less effective in reducing disaster risk as countries become wealthier. We find that, conditional on a disaster occurring, higher incomes generally reduce a country's social vulnerability to such disasters. We additionally find that underlying political structures have an important influence over the human costs of disasters, with outcomes more favorable in democratic societies.

JEL codes: I3, Q5, O2

Keywords: Natural disasters, climate change, economic development, vulnerability

*Corresponding author: pward@purdue.edu. Funding for this research was provided, in part by the Purdue Research Foundation and by the Bureau of Economic Growth, Agriculture and Trade, U.S. Agency for International Development through the BASIS Assets and Market Access Collaborative Research Support Program. The opinions expressed herein are those of the authors and do not necessarily reflect the views of the sponsoring agencies.

[†]Department of Agricultural Economics, Purdue University, 403 West State Street, West Lafayette, IN 47907 USA; phone (765) 494-0848; fax (765) 494-9176; email pward@purdue.edu

[‡]Department of Agricultural Economics and Purdue Climate Change Research Center, Purdue University, 403 West State Street, West Lafayette, IN 47907 USA; phone (765) 494-9672; fax (765) 494-9176; email shivelyg@purdue.edu

1 Introduction

In recent years, economists and others have shown great interest in studying natural hazards, their economic and social impacts, and potential ways to mitigate their effects (e.g. [Guimaraes et al., 1992](#); [Skidmore and Toya, 2002](#); [Shaughnessy et al., 2010](#); [Gassebner et al., 2010](#); [Noy, 2009](#); [Noy and Vu, 2010](#); [Noy and Nualsri, 2011](#)). In this study, we consider the determinants of disasters, in particular the factors that cause extreme natural events to become natural disasters. We follow [Blaikie et al. \(1994, p. 21\)](#), who define a hazard as an “extreme natural event which may affect different places singly or in combination (coastlines, hillsides, earthquake faults, savannas, rain forests, etc.) at different times (season of the year, time of day, over varying return periods, of different duration).” By this definition, many extreme natural events can be classified as natural hazards. These include earthquakes, volcanoes, landslides, droughts, floods, cyclones, and tornadoes. In contrast, a disaster occurs “when a significant number of vulnerable people experience a hazard and suffer severe damage and/or disruption of their livelihood system in such a way that recovery is unlikely without external aid” ([Blaikie et al., 1994, p. 21](#)).

Since 1973, the Center for Research on the Epidemiology of Disasters (CRED) has been compiling a database that tracks both the human and economic tolls that have resulted from natural disasters, including historical evidence dating to the beginning of the twentieth century.¹ CRED data are compiled from many different sources, including United Nations agencies, insurance agencies, non-governmental organizations (NGOs), other research institutions and press agencies. To systematize data collection and to maintain consistency in the EM-DAT database, CRED defines a disaster as a “situation or event which overwhelms local capacity necessitating a request to national or international level for external assistance.”² They use four criteria in characterizing an event as a disaster, namely that (1) ten or more people are reported killed; (2) one hundred or more people are reported affected; (3) a state of emergency is declared; or (4) a call is made for international

¹EM-DAT: The OFDA/CRED International Disaster Database - www.emdat.be - Université Catholique de Louvain - Brussels - Belgium. It could reasonably be argued that, because of the difficulties associated with finding reliable data on disaster mortality and morbidity far into the past, the estimates from early in the twentieth century likely understate the true numbers. As a result, these total numbers may not fully capture the human costs of climate-related disasters.

²See <http://www.emdat.be/glossary>.

assistance.³ In this paper, we focus only on climate-related disasters.⁴ For these, EM-DAT reports in excess of 20 million related deaths and over 6 billion persons affected between 1900 and 2010.⁵ Table 1 reports the decadal totals of persons killed and affected by climate-related disasters from the 1940s through the 2000s.

Perhaps not surprisingly, the number of deaths from climate-related disasters has declined steadily since the 1940s. During this time, advances in physical infrastructure and medical technology have dramatically enhanced countries' abilities to prevent deaths when climatological hazards strike. However, the total number of persons affected (but not killed) by climate-related disasters rose dramatically from the 1950s through the 1990s. Only recently has this upward trend begun to level off. Part of this dramatic increase in the number of affected persons could reflect lower mortality, since some of these affected persons otherwise might have died as a result of these disasters if not for advancements in response and recovery. However the scale of the difference between the number of deaths and the number of affected persons undermines this argument. It might also be suggested that some of these increases are due to general population growth. Strömberg (2007) suggested this as a potential explanation, since larger populations expose more people, thereby increasing the likelihood that a hazard becomes a disaster. However, even after controlling for population growth, the number of affected persons per 1,000 population continued to increase during most of the latter half of the twentieth century, and only in the early years of the twenty-first century has this ratio fallen. Population growth alone, therefore, cannot explain the dramatic increases in affected populations that have been observed in the latter part of the twentieth century.

At least part of the explanation for this increase in the number of affected persons, therefore, must rest with an increase in the number of reported disaster events. Table 2 lists the number of reported disasters by decade and disaster type. These data reveal a dramatic increase in the number of reported disasters since the 1940s. Particularly striking is the increase in the number of flood disasters that have been reported in the last 60 years. The number of reported storm

³See <http://www.emdat.be/criteria-and-definition>.

⁴Using EM-DAT's definitions, the climate-related disasters we consider include droughts, extreme temperatures (both extreme heat and extreme cold), floods, wet mass movements (e.g., landslides or mudslides), and storms (encompassing both tropical storms and localized convective storms).

⁵According to EM-DAT definitions, the total number of affected persons includes those injured, displaced, or otherwise needing immediate attention.

disasters has increased dramatically as well, from about 50 storm disasters in the 1940s to over 1,000 storm disasters in the 2000s. One cannot simply discount the effect of changing climatic conditions on the frequency of climatological hazards. Increasing concentrations of atmospheric carbon dioxide have resulted in warmer air and sea surface temperatures (temperatures today are already 0.8°C above pre-industrial levels), which have had and will continue to have significant adverse effects on evapotranspiration cycles, melting glacial and ice cap regions, thawing arctic permafrost, and oceanic currents and heat-distribution systems. Changing climatic conditions have resulted in less frequent frosts, yet more frequent and more intense heat waves ([World Development Report, 2010](#)). Somewhat counter-intuitively, both floods and droughts are occurring more frequently ([Millennium Ecosystem Assessment, 2005](#), cited in [World Development Report, 2010](#)). Continental interiors, such as the Sahel in Africa or the Mediterranean region in Europe, have experienced more frequent and more intense droughts, despite global increases in precipitation ([World Development Report, 2010](#)). Recent studies have drawn causal linkages between anthropogenic increases in carbon concentrations and extreme climate events, including floods (e.g., [Pall et al., 2011](#)) and increased precipitation (e.g., [Min et al., 2011](#)). Additionally, evidence suggests that the intensities of storms and tropical cyclones has increased ([Webster et al., 2005](#)). The increased frequency of these climate-related hazards, therefore, lends some support to the hypothesis that a rise in the number of EM-DAT climate-related disasters can be linked to changing climatic conditions.

It has been widely argued that global climate change will introduce greater climate variability which in turn will increase mankind's exposure to extreme events, among them intense rainfall (e.g., [Diffenbaugh et al., 2005](#); [Trapp et al., 2007](#)), greater heat stress (e.g., [Diffenbaugh et al., 2005, 2007](#); [Battisti and Naylor, 2009](#)), and more violent storm events (e.g., [Emanuel, 2005](#)). Moreover, atmospheric-oceanic general circulation models (AOGCMs) suggest that the impacts of changing climate conditions are not distributed evenly across the globe. A disproportionate share of the adverse effects of climate change and the associated increases in the frequency and intensity of climate-related hazards are expected to be borne by the world's poor, particularly those in Africa and Asia (e.g., [Battisti and Naylor, 2009](#); [Parry et al., 2007](#); [Tol et al., 2004](#); [Mendelsohn et al., 2006](#); [Allan and Soden, 2008](#)). Additionally, recent analyses of the worldwide populations at high

risk from climate change reveal a disproportionate share in low-income settings (Parry et al., 2007). For this reason, it is important to understand what factors—especially those under the influence of policy—increase or reduce a country’s vulnerability to climate-related disasters.

Below we review a conceptual model introduced by Blaikie et al. (1994) that attempts to explain a society’s vulnerability to disasters. This conceptual model, in conjunction with existing studies examining vulnerability and the determinants of disaster outcomes, provides a series of testable hypotheses that serve as the basis for our empirical exercise. We begin our empirical analysis by exploring the effects of various factors on disaster risk. Using an unbalanced cross-country panel, we estimate a series of random effects panel probit regressions to assess the effect of income, political institutions, and geography on a country’s disaster risk. We then use random effects panel data techniques to test the conceptual relationships between disaster outcomes and the social, economic, and political pressures to identify and measure the extent to which these factors shape social vulnerability to climate-related disasters, conditional upon a disaster occurring.

2 Conceptual Framework

Hewitt (1983) suggested that the social impacts of a disaster depend more on the underlying social structure in which a hazard occurs than the society-environmental interactions in which the hazard takes place. Under this view, vulnerability reflects disruptions to livelihoods, not merely to ecosystems or physical infrastructure (Adger, 1996, 1999; Chambers, 1997). For example, one coastal community may have a high degree of exposure to hurricanes, but if sufficiently endowed with strong institutions may be less vulnerable to these potential shocks than a community relatively insulated from climatic shocks but with a small pool of vulnerable assets and a weak social fabric due to longstanding political, economic, or civil strife.

In an attempt to explain patterns of “social vulnerability”, Blaikie et al. (1994) proposed a conceptual model tracking the progression of vulnerability from socio-economic, political and institutional forces into unsafe physical and social conditions that lead to mortality and morbidity in the event of a natural hazard. This “Pressure and Release” model of disasters conceptualizes a disaster as a complex interaction of two opposing forces: natural hazards and a vulnerable society. Where

there exist both natural hazards and a vulnerable society, the risk of a disaster is significantly greater. But societies are not vulnerable merely because of their *exposure* to hazards. Exposure increases the risk of a disaster, but the vulnerability of a society is a separate force. According to the Pressure and Release model, the vulnerability of a society begins with the social, economic, and political structures and ideologies that shape the distribution of physical, human, social and political capital in a society. This view is consistent with the political economy literature focusing on governmental institutions in disaster preparedness and response (e.g., [Abney and Hill, 1966](#); [Bommer, 1985](#); [Besley and Burgess, 2002](#); [Khandker, 2007](#); [Cohen and Werker, 2008](#)). In essence, these root causes can be conceptualized as a lack of entitlements ([Sen, 1981](#); [Devereux, 1993](#)). The interaction of different social structures and institutions can play a vital role in disaster prevention, even in countries with very low absolute incomes ([Sen, 1999](#)). One of the social institutions that receives the most credit in most analyses is a functioning multiparty democracy. The existence of democratic institutions generally provides transparency in government operations, a free and open discussion of policies and governmental actions without fear of threats and intimidation, an uncensored transmission of information and ideas through the media, and an electoral process which provides incentives for those in power to do all they can to reduce the suffering of their constituents, or risk losing their power altogether. These incentives are not present in dictatorial regimes or under colonialism, where the rulers wield unchallenged power. Political and social institutions such as democracy can therefore be powerful factors influencing both the pre- and post-shock responses to events.

While these root causes may be important determinants of vulnerability, they are neither necessary nor sufficient to result in either a vulnerable society or disasters. Rather, there must be dynamic pressures that translate the root causes into unsafe conditions ([Blaikie et al., 1994](#)). Examples of these dynamic pressures include insufficient local institutions, inadequate training and education of the populace, a lack of local investment in infrastructure, a lack of functioning local markets, a lack of press freedom, rapid population growth, rapid urbanization, onerous debt repayment schedules, deforestation and other ecosystem damage. [Blaikie et al. \(1994\)](#) suggest that rapid urbanization is an especially important factor contributing to vulnerability, since rapid

urbanization in many developing countries puts immense pressure on resources that are already highly constrained. This is perhaps especially true in urban slum dwellings, where residents incur greater risks from landslides, mudslides, and floods because they live in close proximity, often in poorly constructed structures that contribute to soil erosion and the alteration of natural drainage patterns (Blaikie et al., 1994). Macroeconomic forces can also have a significant impact on vulnerability. Structural adjustment programs imposed on many developing countries in the 1980s and 1990s often had unanticipated effects that amplified vulnerability. Because these programs were often imposed on countries facing current account crises, one of their key ingredients was reducing public expenditures. This often required reductions in budgets for education, health, sanitation, and infrastructure. Additionally, interest and charges on loans diverted resources that otherwise might have been spent in ways that reduced vulnerability.

Unsafe conditions are the final progression of forces and factors resulting in vulnerability. These represent the most apparent manifestation of vulnerability in various forms, including fragile physical environments, fragile economies, marginalization, and insufficient public actions. There are several reasons why poorer countries might be more vulnerable to disasters than richer countries on these grounds. By and large, industrialized nations have the ability to cope with climate shocks. Heating and cooling capacity in the industrialized world is generally well-established, allowing some semblance of control over interior environments (although the 2003 European heat wave and Hurricane Katrina provide stark exceptions). Additionally, municipal infrastructure (e.g., roads, bridges, water and sewer systems) is generally robust; public health infrastructure is strong (allowing developed nations to more adeptly deal with disease outbreaks, etc.); social security and other publicly provided safety nets are in place; and communication infrastructure facilitates disaster preparedness and response. So, while heavy rainfall events, for example, are unlikely to be disastrous in developed regions, such events could be devastating in developing countries. The suggestion that income reduces vulnerability to climate change is not new. Schelling (1992), for example, dedicated his American Economic Association presidential address to the economics of climate change, highlighting the merits of economic development as a means of reducing exposure to adverse climate change risks. He suggests that the best defense against climate change for many countries would be

continued economic development. A recent study by [Wheeler \(2011\)](#) supports this hypothesis, finding that per capita income lowers disaster risk even after controlling for factors that may confound the increases in disaster reporting. This contrasts with other recent empirical applications (e.g., [Kahn, 2005](#); [Strömberg, 2007](#)) which suggest that income may not be a significant factor in whether a country experiences a disaster, but that wealthier countries have lower mortality and morbidity when disasters do occur. [Kellenberg and Mobarak \(2008\)](#) suggest a nonlinear relationship between income and disaster outcomes; countries experience increasing disaster deaths until their incomes reach a threshold level, beyond which disaster deaths decline with income.

With climate change expected to increase the frequency and intensity of climate-related hazards, the disaster pressures brought about by the exposure to these hazards are likely to increase. If this is indeed the case, then the only way to withstand the pressures that exacerbate disaster risk is to reduce social vulnerability. While there are indeed some forces in nature that are beyond any reasonable measure a society can take in avoiding them, most hazards would not be classified as catastrophic disasters. In fact, many of the damages would not occur except as a direct result of the social structures that characterize the recipient of the shock. The analysis below is organized to investigate this claim.

3 Data

Our data constitute an unbalanced panel consisting of 1,055 observations covering 103 different countries from 1980 through 2007. These data are compiled from a number of different sources. A complete summary of these sources can be found in [Appendix A](#). We utilize disaster outcome data from EM-DAT, including the number of persons killed and the total number of persons affected, delimited by year, country, and disaster type. While the EM-DAT database tracks disaster outcomes back to 1900, we follow [Kahn \(2005\)](#) and only use disaster outcomes from 1980 onward. Since we are primarily interested in the social outcomes of climate-related disasters, we only consider as disasters those events from which social outcomes (persons affected or killed) were reported. While death outcomes may be thought to demarcate more vulnerable societies from less vulnerable ones, we prefer to emphasize the numbers of affected persons, since these figures may more accurately

reflect the broad impact of a disaster on a society, and since these numbers may be more useful for policymakers in planning for both disaster preparedness and response ([Guha-Sapir et al., 2004](#)). To allow these mortality and morbidity figures to illustrate the disaster footprint on the society, we convert the figures into deaths and affected persons per 1,000 people in the population. Using these figures as a proportion of the population is a departure from previous studies that attempt to identify economic and social correlates of disaster outcomes (e.g., [Kahn, 2005](#); [Toya and Skidmore, 2007](#); [Strömberg, 2007](#)), which instead control for population through the inclusion of a right-hand side covariate. By transforming the disaster outcome variables into proportional measures, we are able to isolate factors that are correlated with a definition of vulnerability that is in terms of a large impact proportional to the population. Changes in national boundaries following the break-up of the Soviet Union can introduce some measurement error. We avoid this potential problem by only using observations on former Soviet states after 1990.

To test the hypotheses suggested by the Pressure and Release model, we use a variety of variables obtained from the World Bank’s World Development Indicators. While it is impossible to isolate data on some of the specific root causes, dynamic pressures, and unsafe conditions identified by the model, we introduce a number of proxy variables to capture the underlying variation in these factors. For example, we are unaware of readily available data on disaster preparedness, the lack of which is identified as an unsafe condition in the Pressure and Release model. In order to control for a country’s degree of disaster preparedness, we use data on the number of physicians per 1,000 people in the population. Additionally, we use information on population density (as a proxy for the degree of urbanization), the population growth rate, the number of telephones per 1,000 people (as a proxy for physical infrastructure; see, for example, [Quazi, 2007](#); [Asiedu, 2002](#); [Loree and Guisinger, 1995](#)), and real per capita GDP (constant 2000 \$US). To control for presence of marginalized social groups, which may produce unsafe conditions, we incorporate a dependency ratio measure as well as an ethnic fractionalization measure reported in [Alesina et al. \(2003\)](#). The dependency ratio measures the ratio of dependents (people younger than 15 or older than 64) to the working-age population (those aged 16-64). The ethnic fractionalization measure essentially captures the probability that any two individuals in the population will have

different ethnic roots. Country fractionalization scores approaching zero are indicative of highly homogeneous societies, while country fractionalization scores approaching one are indicative of highly heterogeneous societies. A low degree of ethnic fractionalization is likely to result in higher degrees of marginalization for minority groups.

Additionally, we use data from various sources to control for the social, political, and economic structures that serve as root causes of vulnerability.⁶ To control for political structures and ideologies, we use a measure of democracy and autocracy obtained from the Polity IV project.⁷ Following [Kahn \(2005\)](#), we convert this index to take on the values 0–20, where higher scores represent a more democratic political structure. To proxy for access to political power, we use an index of political rights from Freedom House’s Freedom in the World country rankings.⁸ Originally, the index of political rights was specified on a scale of one to seven, with one indicative of a high degree of political rights and seven indicative of few political rights. To facilitate easier interpretation of the results, we reformulate the index such that a higher score indicates a higher degree of political rights. To control for limited access to resources and economic capital, we use a Gini coefficient measure described in [Deininger and Squire \(1996\)](#). Most data on Gini coefficients are very sparse, and therefore including a large number of observations for a particular country while also controlling for time-varying income inequality can prove difficult. The Gini coefficient data used in this analysis is compiled from many different sources of varying degrees of reliability. The data published in [Deininger and Squire \(1996\)](#) use only high quality estimates of income inequality, but Internet sources provide other, mixed quality estimates that are reported with much greater frequency. As such, there may be multiple estimates for a particular country-year combination, with each of the estimates resulting from a different source or study. In order to accommodate the most accessible data, we use country averages of the mixed quality Gini coefficients over the period 1980-2007.⁹ To control for economic structures and ideologies, we use a measure of economic openness (exports

⁶[Wheeler \(2011\)](#) notes that social and political structures could also control for the quality of disaster reporting. To this end, he incorporates variables that purport to capture quality in reporting as well as quality in the regulatory environment. We do not explicitly control for these factors, but incorporating democracy and political rights should capture a substantial portion of these effects.

⁷See <http://www.systemicpeace.org/polity/polity4.htm>. These data were accessed on 28 January 2011.

⁸See <http://www.freedomhouse.org/template.cfm?page=439>. These data were accessed on 22 December 2010.

⁹See <http://go.worldbank.org/UVPO9KSJJ0>. These data were accessed on 28 January 2011.

plus imports as a share of real GDP) obtained from the Penn World Tables, v. 6.3 (Heston et al., 2009).

To control for the effects of geography, we use information on elevation, latitude (absolute value), and the proportion of a country’s land area within 100 kilometers of an ice-free coast, obtained from the Center for International Development.¹⁰ We control for land area (square kilometers) using data from the World Bank’s World Development Indicators. We account for spatial heterogeneity with regional indicator variables at the sub-continental level.¹¹

4 Empirical Models and Results

Following Kahn (2005), Strömberg (2007) and Wheeler (2011), we measure the relationship between disaster risk and a range of factors associated with economic development and institutional characteristics. We quantify disaster risk as the probability of experiencing a climate-related disaster.¹² Modifying the empirical approach in Kahn (2005), we consider a simple probit model of the form:

$$\text{Prob}(D_{ijt} = 1) = F(\text{Geography}_j, \text{Area}_j, \text{Income}_{jt}, \text{Institutions}_{jt}, t) \quad (1)$$

where $\text{Prob}(D_{ijt} = 1)$ is the probability that a disaster of type i will occur in country j during time period t , Geography_j is a time-invariant vector of geographical characteristics,¹³ Area_j is a time-invariant land area measure, Income_{jt} is a time-varying measure of real per capita GDP, Institutions_{jt} is a potentially time-varying vector of characteristics regarding the underlying political and institutional structure, and t is a time trend. The link function $F(\cdot)$ is the normal

¹⁰See <http://www.cid.harvard.edu/ciddata/geographydata.htm>. These data were accessed on 28 January 2011. Country latitudes are evaluated at the geographic centroid of the country. Elevation measures represent the mean elevation in meters above sea level.

¹¹Kahn (2005) and Strömberg (2007) use a set of continental dummy variables. We allow for a greater degree of heterogeneity by including dummy variables for North America, Central America, South America, the Caribbean basin, the European Union countries, other Europe, the former Soviet Union, the Middle East and North Africa, Sub-Saharan Africa, Australia/New Zealand, South Asia and Southeast Asia.

¹²The study by Wheeler (2011) uses a different definition of disaster risk. In his study, reported disaster risk was computed as the log-odds ratio of the proportion of the population affected by an extreme weather event.

¹³This vector of geographic characteristics includes the absolute value of latitude, elevation, the proportion of land near an ice-free coast, and regional dummy variables.

cumulative distribution function.¹⁴ We allow for a nonlinear relationship between per capita income and disaster risk by using the natural logarithm of income instead of income levels. We use a random effects approach to estimate this model.¹⁵

We begin by estimating the effects of geography, land area, income, political structures and time on the probability that country j experiences any of the climate disasters identified above. This is perhaps the broadest measure of climate-related disaster risk, since it does not distinguish among the specific types of disasters. A full set of random effects probit models were estimated, but we report only the results of the least restricted model in column (1) of Table 3. The findings reported in column (1) of Table 3 are somewhat consistent with those of [Kahn \(2005\)](#) and [Strömberg \(2007\)](#), but are contrary with those of [Wheeler \(2011\)](#). While we obtain a negative coefficient for per capita GDP, this point estimate is not statistically different from zero at standard test levels, which suggests that per capita income does not significantly affect a country’s risk of encountering a natural disaster.

We find that more democratic societies are no less likely to experience a climate disaster than autocratic societies. This may result from countervailing forces. In democratic societies there is typically a greater degree of transparency in governmental operations, so politicians in democratic societies have much greater accountability than politicians and bureaucrats in autocratic or totalitarian societies, and because of this increased accountability these politicians face have much greater incentives to implement the necessary preparations to prevent a natural hazard from becoming a natural disaster. Democracy would therefore be expected to lower disaster risk. On the other hand, the additional transparency and better regulatory conditions found in democratic

¹⁴Note that our binary dependent variable indicates whether a county experienced at least one disaster in a particular year. Many countries experienced more than one disaster in a given year.

¹⁵We use a random effects panel probit model for several reasons. First, and most importantly, random effects are used because the conditional likelihood approach necessary for estimation of the fixed effects model does not yield computational simplifications, as there does not exist a sufficient statistic allowing the fixed effects to be conditioned out of the log-likelihood function ([Baltagi, 2001](#)). Attempting to maximize the likelihood function over all of the parameters, including the fixed effects, in general leads to inconsistent estimates. The lack of a fixed effects estimator renders Hausman specification tests impossible. Second, even if it were possible to estimate a fixed effects probit model using a minimally sufficient statistic for the fixed effects error component, it would be impossible to estimate the effects of any time-invariant explanatory variables (such as geographical characteristics) in a probit setting. While instrumental variables could be used in a linear fixed effects regression setting, such as a linear probability model, there are no alternatives within nonlinear probability models. The limitations of linear probability models have been thoroughly explored. Finally, random effects are more appropriate considering the highly random nature of climate-related hazards.

societies may improve the reporting of disasters.¹⁶ [Kahn \(2005\)](#) also suggests that the declaration of national emergencies may be influenced by political motives or may be made in repayment for electoral favors. Such political motives would not be present in autocratic political systems. This characteristic of democracy would be expected to increase the probability of a disaster being reported. The sum of these two opposing forces of democracy may ultimately result in there being no statistically significant relationship between the quality of a country’s democratic institutions and its probability of experiencing a climate-related disaster.

We can assert with a high degree of certainty that geographical factors play an important role in determining a country’s vulnerability. Larger countries are substantially more likely to experience disasters, as are those with a larger proportion of area within 100 km of an ice-free coast and a higher average elevation. Additionally, the point estimate associated with the time trend is highly significant, suggesting that countries have been increasingly more likely to experience (and report) climate-related disasters over time. Surprisingly, countries in North America, the European Union, and Australia/New Zealand are no less likely to experience a disaster than countries in Sub-Saharan Africa, at least not once accounts for the level of per capita income. Countries in South and Southeast Asia are each roughly 45% more likely to experience a disaster than countries in Sub-Saharan Africa.

We next consider how these factors affect the probability of a country experiencing each of the various climate-related disasters in isolation. This may be of particular interest if the regional impacts of climate change are such that the frequency of a specific type of disaster can be expected to increase. Here, we present only the estimates from the unrestricted model, within which all other restricted models are nested. These results are reported in columns (2)–(6) in [Table 3](#). These results allow us to make several observations. First, while income may not significantly affect the risk of broadly-defined climate disasters (i.e., column (1)), it does affect risk for several disaster types. Wealthier countries are less at risk of drought disasters, as an additional 1% increase in income lowers the risk of a drought disaster by roughly 3%. An additional 1% of per capita income

¹⁶[Wheeler \(2011\)](#) includes variables for “Voice and Accountability” and “Regulatory Quality” in his disaster risk assessment, suggesting that these control for differences in reporting quality that might otherwise confound the correlations.

raises the risk of extreme temperature disasters by about 0.8%. Of the 318 extreme temperature events that are recorded in the data (including cold waves, extreme weather conditions, and heat waves), nearly 42% were reported from Europe.

Although none of the regional coefficients are significantly different from zero in the drought model, nearly all are negative, suggesting that countries in most regions are less likely to suffer drought disasters than countries in Sub-Saharan Africa.¹⁷ Countries in South Asia are significantly more likely to experience all of the disaster types except droughts. Most of the regional dummies have positive and statistically significant coefficients in the wet mass movement model, suggesting most countries are significantly more likely to experience these types of disasters than those in Sub-Saharan Africa.

As before, geographical characteristics are important determinants of disaster risk for the various disaster types. Countries with larger land areas are more likely to suffer each of these various disaster types. Countries with a higher elevation are significantly more likely to suffer landslides and mudslides. Countries further away from the equator are less likely to experience floods and wet mass movements, but more likely to experience storms. Having a relatively large proportion of land in close proximity to the sea increases the probability that a country will experience droughts and storms, as well as generically defined climate disasters, but there is no discernible effect on the probability of experiencing any of the other disaster types.

In general, these results suggest that a higher real per capita income does not lower a country's probability of experiencing a climate-related disaster, even after controlling for characteristics that are presumably the prime geographical determinants of exposure to climate-related hazards. Rather, for certain disaster types, richer countries are *more* likely to experience a reported disaster than poorer countries. However, a somewhat different story emerges when we consider the effects of income at different income levels. To see this, we classify countries in the sample as high-, middle-, and low-income based on World Bank classifications, and interact these classifications with real per capita real GDP.¹⁸ We then re-estimate equation 1 using the combined disaster binary outcome as

¹⁷These results are not reported in Table 3.

¹⁸World Bank classifications break middle-income countries into an upper-middle-income and lower-middle-income subsets. We combine these two into a single category.

the dependent variable. Incorporating the interaction terms in this fashion allows us to isolate the effect of income on reducing disaster risk at various income levels. The results from this regression are shown in column (7) of Table 3. We can compute the marginal effect of income and evaluate these marginal effects at different income levels (i.e., for different values of the income classification variables) to assess how the effect of income varies. These results suggest a nonlinearity in the effect of income on lowering disaster risk. For low income countries, an additional 1% of income lowers disaster risk by about 8%, marginally significant at test levels just outside standard levels. As per capita income levels increase, additional income has a marginally decreasing effect on lowering the probability that a country will experience a disaster (that is, the point estimates for the marginal effects become smaller as countries progress to the middle- and high-income levels) and the statistical significance of these estimated marginal effects also diminish.¹⁹ As might be expected, these results suggest that continued economic development is an important factor in reducing disaster risk, but economic development reduces disaster risk only for poor countries. Once a country attains middle-income status additional income no longer reduces disaster risk.

Additionally, we find that higher wealth reduces the probability that a country will experience a catastrophic disaster. We define a catastrophic disaster as one in which the death count or count of affected persons exceeds the 90th percentile of all outcomes. Since many countries experience more than one disaster in a given year, we use the average number of deaths or affected persons per disaster. This model is estimated as:

$$\text{Prob}(C_{jt} = 1) = F(\text{Geography}_j, \text{Area}_j, \text{Income}_{jt}, \text{Institutions}_{jt}, t) \quad (2)$$

where $\text{Prob}(C_{jt} = 1)$ is the probability that a catastrophic disaster will occur in country j during time period t . We present the results of these regressions in Table 4. From these results we see that a rise in per capita income reduces the probability that a country will experience a catastrophic disaster leading to either a large number of deaths or a large number of persons affected. An additional 1% of income lowers the probability that a country will experience a catastrophic disaster leading to a large number of affected persons by roughly 2.8%, while an additional 1% of income

¹⁹For these marginal effects, the standard errors have been computed using the delta method.

lowers the probability of a catastrophic disaster leading to a large number of deaths by nearly 2%. The effect of time differs across these two models. The probability that a catastrophic disaster will affect a large number of persons appears to be increasing over time, but the probability that a catastrophic event will result in a large number of deaths is roughly constant over the time period covered by our data. The positive time trend for the affected persons regression is consistent with the general increase in both the number of disasters and the number of affected persons over time. Not surprisingly, larger countries are more likely to experience a catastrophic disaster, as are countries that have a higher proportion of their land area within 100 km of ice free coasts.

Are there reasons to believe that disaster risk might translate into social vulnerability, measured in terms of the social impact of a disaster? To identify countries at high risk, we use the predicted probability of a climate-related disaster, based on column (1) of Table 3. We compute a country-specific average predicted disaster probability using all available observations for each country and use this as a proxy for a country’s underlying disaster risk. To gauge social vulnerability, we consider the number of persons killed or affected by climate-related disasters per 1,000 people in the population. Figures 1 and 2 plot the probability of disaster against each of these two measures of social vulnerability. From Figure 1, we see that countries with higher disaster risk also typically have a higher number of deaths resulting from climate-related disasters. A similar story emerges from Figure 2; countries with higher disaster risk have, on average, more people affected as a result of climate-related disasters. If we interpret these bivariate probability contour plots as defining the relationship between disaster risk and social vulnerability, then these figures also allow us to determine which countries are more vulnerable overall than they would appear to be based solely on a measure of disaster risk. The dashed lines in Figures 1 and 2 correspond to the average relationship between disaster risk and social vulnerability in the data generated by simple bivariate linear regressions. Points above this line represent countries with higher rates of social disaster outcomes than would be predicted by the average disaster risk, while points below this line represent countries with lower rates of outcomes than would be predicted by the average disaster risk. As an example, Canada (CAN) has an average disaster risk of 88.7%: on average, based on Canada’s geographical characteristics, average per capita income, and the parameter estimates from

column (1) of Table 3, we would expect Canada to experience a climate-related disaster roughly nine out of every 10 years. In terms of the death rates arising from such disasters, the observed death rates are below what would be expected, given this high disaster risk. Based on the simple bivariate linear regression represented by Figure 1, we would expect Canada to have, on average, about 0.002 deaths per 1,000 people per year. In reality, we observe an average of less than 0.00014 deaths per 1,000 people per year. A similar story emerges when we consider social vulnerability in terms of persons affected by climate disasters. Based on the simple bivariate linear regression represented in Figure 2, we would expect roughly 4 Canadians to be affected per 1,000 people per year. Canada’s observed rate of affected persons, however, is less than 0.1 per 1,000 people per year.

While Canada and other countries that lie below the dashed lines in Figures 1 and 2 may be *less* socially vulnerable than would be expected given underlying disaster risk, other countries are *more* socially vulnerable than disaster risk would indicate. These countries lie above the dashed lines in these figures. Many of these countries’ characteristics lead to relatively low measures of disaster risk. However, the social outcomes of disasters are more severe than average for that particular level of disaster risk. In both figures, Swaziland (SWZ) stands out as a country significantly more socially vulnerable than would be predicted based solely on its disaster risk. Based on model estimates, we predict an average annual disaster risk of only 8.5% for Swaziland. Based on the bivariate linear regression estimates, however, we predict that a country with a disaster risk of 8.5% should have a disaster-related death rate less than 0.0001 per 1,000 people in the population. We observe, however, more than 0.02 deaths per 1,000 people in Swaziland on average. Additionally, Swaziland suffered, on average, more than 367 persons affected by climate-related disasters per 1,000 people in the population, a number far greater than would be expected based on its low disaster risk (less than 0.1 affected person per 1,000 people in the population).

The contour lines in these figures trace out the two dimensional contours resulting from the three dimensional nonparametric kernel estimation of the bivariate densities. These contours provide a sense of the shape of the joint distribution of disaster risk and social vulnerability in our data, which also facilitates identification of countries that have disaster risks or disaster outcomes in the tails

of this joint distribution. Figure 1, for example, is bi-modal. There is a mass of countries with an underlying disaster risk of about 0.5, but with rather low average death rates from disasters. There is also a second, less prominent mass representing countries with a significantly higher underlying disaster risk. Both modes, it should be noted, lie below the regression line, indicating that the greatest frequencies of observed countries should be less vulnerable to climate disasters than would be predicted based solely on disaster risk. It should also be noted that several countries lie outside the 5% contour line, suggesting that these countries lie outside the 95% confidence interval for this joint distribution. These observations can be considered in the tails of the joint distribution. Swaziland, Honduras (HND), Nicaragua (NIC), and Bangladesh (BGD) are in the upper tail of the joint distribution, indicating an extreme disparity between disaster risk and social vulnerability, where the social vulnerability to climate disasters is well beyond what would be expected based on the country's underlying disaster risk. Canada, on the other hand, is in the lower tail of the joint distribution. While Canada has a high disaster risk, the social outcomes resulting from disasters are well-below what would be expected based on disaster risk alone. There are no observations in the tails of the joint distribution in Figure 2, but the single mode of the joint distribution lies above the regression line, indicating that a high frequency of observations are more socially vulnerable (in terms of the rate of affected persons) than would be predicted based on disaster risk alone.

In Figure 2, both China (CHN) and India (IND) appear in the upper right-hand corner, indicating both a high disaster risk and a high degree of social vulnerability. This is consistent with [Wheeler \(2011\)](#), who ranks China and India as the first and third most vulnerable countries to extreme weather events by 2015. However, when vulnerability is defined in terms of death rates (i.e., Figure 1), we find that China is less vulnerable to climate-related disasters than would be predicted based on disaster risk alone, while India is no more vulnerable than disaster risk alone would suggest. Rather, countries like Bangladesh, Nepal (NPL), the Philippines (PHL) and Vietnam (VNM) appear to stand out as especially at-risk and also highly vulnerable.

It is worth noting that 41% of Sub-Saharan African countries and 80% of South Asian countries are above the regression line in Figure 1, while 72% of Sub-Saharan African countries and 60% of South Asian countries are above the regression line in Figure 2. This is perhaps suggestive

of two stylized facts. First, while the results are suggestive of a positive relationship between disaster risk and social vulnerability, these two concepts are distinct. Disaster risk is a function of, among other things, exposure to climate-related hazards. In the case of Sub-Saharan Africa, disaster risk is generally rather low. But simply because a country’s geographical characteristics are such that they are not particularly prone to climate disasters does not imply that they are less vulnerable to the adverse social effects of these disasters. For many countries in Sub-Saharan Africa, their characteristics are such that the probability of experiencing a disaster is low, yet the social outcomes from realized disasters are large. Because many countries in Sub-Saharan Africa have larger social impacts from climate-related disasters than would be predicted solely by their disaster risk, it can reasonably be argued that Sub-Saharan Africa is particularly vulnerable to climate events, even when we consider only the impacts of *extreme* climate events and ignore increasing *mean* temperatures and precipitation levels. Second, some countries have a high degree of risk as well as a high degree of social vulnerability. South Asian countries in particular tend to fall into this category. All countries in South Asia have very high underlying disaster risk, yet the social outcomes from disasters for many South Asian countries are still greater than would be expected based on disaster risk. This suggests that perhaps South Asia is also particularly socially vulnerable to climate change, which is particularly disconcerting considering recent predictions about the potentially large impacts of climate change on these regions (e.g., [Battisti and Naylor, 2009](#); [Parry et al., 2007](#); [Tol et al., 2004](#); [Mendelsohn et al., 2006](#); [Allan and Soden, 2008](#)).

With the relationship between disaster risk and social vulnerability established, we now proceed to test the hypotheses put forward in the Pressure and Release Model. In particular, we aim to examine how a country’s level of economic development (measured in terms of real per capita GDP) affects social vulnerability. The model considers low income levels an unsafe condition, and therefore, poverty itself as a manifestation of vulnerability. Other studies have found that higher incomes lower mortality and morbidity resulting from natural disasters (e.g., [Kahn, 2005](#); [Strömberg, 2007](#); [Toya and Skidmore, 2007](#)), although most of these other studies consider geological disasters (e.g., earthquakes, volcanoes) that we do not include here. Figure 3 plots the average number of deaths per 1,000 people against average real per capita income. This simple plot reveals

no significant relationship between per capita income and the social footprint of disasters. However, a different story emerges when we consider a broader classification of disaster outcomes. Figure 4 plots the average number of persons affected per 1,000 people against average real per capita income. Here, at least so far as can be determined by a simple bivariate analysis, we find evidence of a negative correlation between per capita income and disaster outcomes, a relationship consistent with earlier empirical studies as well as the conceptual framework presented by [Blaikie et al. \(1994\)](#).

To proceed with testing the hypotheses of the Pressure and Release Model, we begin by sequentially examining each of three stages in the progression of vulnerability and then proceed to examine a complete model containing all factors included in each of the preceding stages. For each of the three stages and the complete model, we examine the effects of a vector of time-varying covariates (x'_{it}) and a vector of time-invariant covariates (z'_i) on the two measures of social vulnerability previously introduced (the number of persons killed or affected per 1,000 people in the population), conditional upon a disaster occurring. The disaster outcome figures represent totals from all climate-related disasters that a country experiences in a given year. This “punishes” countries that have multiple disasters with significant social footprints by according them a higher measure of social vulnerability. Despite a disaster occurring, there need not be a nonzero social outcome, since deaths and affected persons are mutually exclusive outcomes in the EM-DAT data. Because we take a logarithmic transformation on these disaster outcomes, we add a unit to each of the counts of deaths and persons affected. Since these mortality and morbidity measures are then divided by the country’s population (in thousands), this unitary addition does not significantly affect these disaster outcome measures. By computing these ratios in terms of population, we can gauge how greatly these disasters have impacted the social fabric of these countries. Since these figures represent the social outcomes of disasters, they can be thought of as *ex post* measures of social vulnerability to climate related disasters. The regressions take the general linear form:

$$\ln \left(\frac{Deaths_{it} + 1}{Population_{it}/1,000} \right) = x'_{it}\beta + z'_i\gamma + \delta t + \nu_i + u_{it} \quad (3a)$$

$$\ln \left(\frac{Affected_{it} + 1}{Population_{it}/1,000} \right) = x'_{it}\beta + z'_i\gamma + \delta t + \nu_i + u_{it} \quad (3b)$$

where $Deaths_{it}$ and $Affected_{it}$ are, respectively, the numbers of persons killed and affected by climate disasters in country i during year t , $Population_{it}$ is country i 's population in period t , t is a time trend variable, ν_i and u_{it} are time-invariant and time-varying error components, respectively, and β , γ and δ are vectors or scalars of parameters to be estimated. To estimate these parameters, we again employ a random effects panel regression.²⁰

We begin by testing the correlation between the unsafe conditions, which are presented as manifestations of vulnerability, and our measure of social vulnerability represented by the disaster outcomes. These results are presented in Table 5, columns (1) and (2). We find a generally strong correlation between these unsafe conditions and social vulnerability, with signs that would generally be expected based on the conceptual model. However, we find that different unsafe conditions are correlated with different dimensions of social vulnerability at statistically significant levels. Per capita income, for example, lowers the societal impact of disasters in terms of persons affected by disasters, but has no measurable effect on the impact in terms of deaths. The insignificance of per capita income on disaster death impacts is contrary to the findings of [Strömberg \(2007\)](#), [Kahn \(2005\)](#), and [Toya and Skidmore \(2007\)](#), who each find a statistically significant negative relationship between a country's level of real per capita income and death tolls from disasters. Several factors differentiate our approach from those of previous work. First, all three previous studies measure the disaster impacts in raw mortality numbers, rather than in terms of a proportion of the population. While previous approaches control for population size through the use of an independent variable, the ensuing coefficient estimates capture the relationship between the explanatory variables and the total disaster mortality, which may not truly reflect a state of social vulnerability. Second, the unit of analysis varies somewhat across studies. For example [Strömberg \(2007\)](#) uses a natural disaster as the unit of analysis, whereas we use country-year observations as the unit of analysis.

Using disasters as the unit of analysis and drawing a correlation between per capita income and the

²⁰Hausman tests indicate a random effects specification over a fixed effects specification. This is sensible considering the random nature of climate hazards applied to the countries in this sample. Additionally, incorporating random effects in lieu of fixed effects allows us to more easily gauge the marginal effects of time-invariant explanatory variables, such as the country average Gini coefficient.

disaster outcome does not account for the fact that certain countries experience multiple disasters in a given year. Hypothetically, each disaster may have a relatively low death toll, and in the full sample these death tolls may, on average, be negatively correlated with per capita income. When the death tolls are summed together during a given year, however, the societal impact of all of the disasters may be rather substantial, and the negative correlation between this social outcome and income may disappear. Our findings suggest that the observed decline in death tolls arising from natural disasters are generally independent of per capita income levels. While this result may be somewhat surprising, it is generally consistent with the bivariate relationship shown in Figure 3.

The effect of social marginalization also appears differently across the two specifications of social vulnerability. A high dependency ratio is significantly correlated with a higher social impact from climate disasters in terms of deaths, but this effect is not statistically different from zero when social vulnerability is measured in terms of persons affected by climate disasters. Since the young and the elderly may be considered particularly vulnerable members of vulnerable societies, it is perhaps not surprising that a higher relative proportion of these vulnerable segments is correlated with a higher death impact from climate disasters. The other measure of marginalization considered, ethnic fractionalization, is negatively correlated with the rate of affected persons, but not significantly correlated with death outcomes. These findings suggest that more heterogeneous societies have lower disaster impacts than homogeneous societies. We believe it likely that, in more homogeneous societies (that is, countries with a low degree of ethnic fractionalization), it is much more likely that political and economic power is concentrated in the hands of a particular ethnic majority, and it is therefore much more likely that a minority group will be marginalized and placed at risk. In very ethnically heterogeneous societies, it may be more difficult for any one ethnic group to gain a plurality in the government and marginalize other ethnic groups.

We next test the relationship between dynamic pressures and our measures of social vulnerability. The results of these models are reported in Table 5 in columns (3) and (4). Due to a general lack of data, we are unable to control for the full range of high-level forces identified as dynamic pressures by [Blaikie et al. \(1994\)](#). Nevertheless, we use data for population pressures (specifically, population density, as a proxy for rapid urbanization, and population growth). We

find very little evidence of a robust statistical relationship between these population pressures and social vulnerability. The absence of a population density effect is contrary to [Kahn \(2005\)](#), who finds a statistically significant negative relationship between average population density and disaster death tolls using a zero-inflated negative binomial estimation approach. One would expect that higher population concentrations—such as in densely populated urban areas—would imply a greater number of vulnerable people, which would then imply a greater disaster death toll, other things equal. Our findings suggest that once the disaster impact is framed as a proportion of the population, these population pressures have little effect on underlying social vulnerability.

In testing the root causes of social vulnerability, we again find some strong support for the hypotheses proposed in the Pressure and Release model. These results are reported in columns (5) and (6) of Table 5. Consistent with previous literature and expectations, we find that more democratic societies have lower degrees of social vulnerability.²¹ While these point estimates are only marginally significant when vulnerability is framed in terms of persons affected by climate disasters, the negative effect is robust across model specifications. We find that countries with a higher degree of average income inequality (measured by a country average Gini coefficient) are more vulnerable in terms of disaster death rates, but no more vulnerable in terms of the rate of persons affected by climate disasters. If we interpret income inequality as indicative of unequal access to resources and power, then these results suggest that higher concentrations of wealth and power result in a more vulnerable society.

Finally, we a full model that incorporates each of the variables included in the three preceding stage regressions. These results are reported in columns (7) and (8) of Table 5. We note that all significant point estimates from the individual stage models carry over to the full, unrestricted model, though not always with the same magnitude. The dependency ratio, for example, remains significantly and positively related to death outcomes, but the magnitude of the point estimates is significantly lower once we account for dynamic population pressures and the social, political, and economic institutions and ideologies that contribute to vulnerability. Nevertheless, incorporating

²¹[Strömberg \(2007\)](#) includes both democracy and government effectiveness in his empirical analysis. He finds that countries with effective governments have lower disaster death tolls, while countries with higher degrees of democracy have higher disaster death tolls.

all of these factors and pressures into a comprehensive model allows us to interpret with a greater degree of clarity which factors are significantly correlated with various disaster outcomes. We again find that countries with higher per capita incomes have lower levels of social vulnerability, while countries with more unequal income distributions have a higher degree of social vulnerability, at least in terms of death outcomes. Taken in tandem these results suggest that wealthier countries with a more equal distribution of resources tend to be the least socially vulnerable to climate-related disasters. Wealthy countries with a higher degree of income inequality are more socially vulnerable than these rich, egalitarian countries, while poor and very unequal societies tend to be the most vulnerable. More democratic societies are generally less socially vulnerable, though the statistical support for this claim is weakened in the complete model.

Across several of these models, we find a positive and significant time trend for social vulnerability in terms of persons affected by climate disasters. For the full model, we find that, with each unit time step, a country can expect roughly one additional person per 1,000 in its population to be affected by climate-related disasters, *ceteris paribus*. This additional social impact, completely independent of population growth, is simply a function of time, and can only be explained by either more thorough reporting over time, an increase in events, or some combination of the two. It is consistent with the observed upward trend in the number of persons affected as a proportion of the population.

The full model also suggests that greater political rights are positively correlated with our social vulnerability measures. This seems counterintuitive, particularly when taken in the context of the findings that more democratic societies generally have lower social vulnerability. While we note that this relationship is only marginally significant across models, we believe, but cannot test, that this result reflects the underlying nature of observed disaster outcomes, namely that to appear in the EM-DAT dataset, the event must be reported. As such, these estimated coefficients may be capturing a positive effect which indicates that the populace in countries with more political rights may be more likely to report disaster mortality and morbidity, or may demand more action from their elected officials. This would then be reflected in higher disaster impacts. In democratic societies, citizens that live in the voting districts of powerful politicians or who live in districts that

support the current administration may be more likely to receive governmental disaster assistance.

Interestingly, we find that countries that are more open to international trade have higher levels of social vulnerability. This result is robust across model specifications and under various restrictions, and so cannot simply be ignored as an aberration. This finding is contrary to [Toya and Skidmore \(2007\)](#), who find that openness to trade significantly reduces death tolls resulting from natural disasters.²² This is also seemingly in contradiction to the conventional wisdom regarding the benefits of trade liberalization. There is by now a vast literature suggesting that trade liberalization promotes economic growth and reduced poverty (see, for example [Dollar, 1992](#); [Ben-David, 1993](#); [Sachs and Warner, 1995](#); [Frankel and Romer, 1999](#); see [Rodriguez and Rodrik, 2001](#) for a critique of this literature). What could be the reason for this rather counterintuitive result? Critiques of the trade and growth literature often suggest that trade does not necessarily promote growth, but rather that other macroeconomic policies which coincide with trade liberalization conflate the interpretation of trade effects. One reason why increased openness to trade may not necessarily contribute to growth in per capita incomes is that such increased openness to trade is often accomplished through the exportation of primary commodities, including natural resources. While this may contribute to an increase in the trade share of GDP, it does not necessarily translate into increases in per capita income. Additionally, dependence on resources can translate into the “resource curse”, which is often explained in terms of rent-seeking behavior. This rent-seeking behavior may generally explain why resource dependent countries also tend to have poor political and social institutions. If the increased social outcomes that were attributed to general openness to trade were in fact due to resource dependence, then one would expect the effect of openness on social vulnerability to either lose statistical significance or change signs when one controls for resource dependence. We find no support for this hypothesis. Even after controlling for resource dependence, we find that openness to trade is still positively correlated with social disaster outcomes.²³

²²When we, like [Toya and Skidmore \(2007\)](#), use raw disaster outcome numbers (instead of rates), we find a statistically significant negative relationship between openness to trade and these social outcomes. This suggests that openness to trade is correlated with lower raw tolls in countries, but positively correlated with the societal impact of disasters.

²³To control for resource dependence, we consider agricultural raw material exports, fuel exports, and ore and mineral exports as a share of GDP. The data used to construct this resource dependence term were obtained from the World Development Indicators. These data were accessed on March 11, 2011.

As an additional explanation, we note that many poor countries received concessionary loans from the International Monetary Fund (IMF) during the 1980s and 1990s. Many of these were coordinated under the Fund’s Structural Adjustment Facility (SAF) or Enhanced Structural Adjustment Facility (ESAF). These concessionary loans often carried conditions aimed at strengthening the recipient countries’ external balances and macroeconomic stability. Policy prescriptions for these countries included fiscal discipline, tax reform, interest rate liberalization, privatization, deregulation, and trade liberalization specifically aimed at export promotion. One of the unintended consequences of these policies was a reduction in health and education expenditures (coinciding with a general reduction in public expenditures) and an increase in unemployment (due to the privatization of state-owned enterprises), both of which can contribute to higher social vulnerability. But as a result of trade liberalization, many of these recipient countries also had significant increases in trade volumes and openness to trade measures, which could generate a positive correlation between openness to trade and social disaster impacts. To test this hypothesis, we interact a country’s openness to trade with a binary variable equal to one in the year a country received an IMF SAF/ESAF loan and all subsequent years (to allow for the persistent effects of these policies). We find that under both specifications for the dependent variable, the structural adjustment effect does not significantly alter disaster outcomes, and the positive relationships between openness and disaster outcomes remain.

We conclude that this correlation reflects a more general relationship between openness and engagement with the international community. Countries that have a high degree of openness to trade are more likely to welcome international assistance, including the involvement of international humanitarian and disaster relief organizations. For example, [Strömberg \(2007\)](#) finds that greater trade volumes are positively correlated with both the provision of humanitarian assistance and the amount of assistance that is provided. Since one criterion CRED uses in defining events as disasters is whether a call for international assistance is made, general openness may lead to an increased frequency of reported disasters and disaster outcomes.

5 Concluding Remarks

In this paper we have examined factors correlated with climate-related disaster risk and social vulnerability. Consistent with previous research, we find that, in general, wealthier countries are no less likely to experience a climate-related disaster than poor countries, once we control for geographical characteristics and regional dummy variables that can be expected to capture exogenous exposure to climate hazards. However, when we examine the effects of income at different income levels, we find that a proportional increase in income reduces disaster risk more for poor countries than for rich countries. These results suggest that continued economic development is a meaningful strategy for poor countries to follow in protecting themselves against disaster risk. Additionally, we find strong statistical evidence that wealthier countries are less likely to suffer catastrophic climate disasters in which either a large number of persons are killed or otherwise affected by the disaster.

Using predicted probabilities from random effects panel probit regressions, we theorize a linear relationship between disaster risk and social vulnerability, where social vulnerability is gauged as the societal impact of a climate-related disaster on a country. In this analysis, we measure social vulnerability as the number of persons killed or otherwise affected by climate-related disasters per 1,000 people in the population. Simple bivariate analysis reveals that, on average, countries with higher average disaster risk are more socially vulnerable to climate-related disasters. Many countries in Sub-Saharan Africa and South Asia are more socially vulnerable to climate disasters than would otherwise be predicted based solely on the underlying disaster risk. Countries in Sub-Saharan Africa do not, in general, have a very high underlying disaster risk. Nevertheless, when disasters strike, the social outcomes resulting from these disasters can be severe. Countries in South Asia, on the other hand, have very high disaster risk, no doubt due to frequent cyclones and flooding. Yet even despite this high disaster risk, the social outcomes resulting from these disasters are generally much higher than would be expected based solely on higher underlying risks.

The Pressure and Release model, first introduced in [Blaikie et al. \(1994\)](#), makes some rather unambiguous claims regarding the progression of social vulnerability. The model suggests that root causes and dynamic pressures lead people to live or work in unsafe conditions. These unsafe conditions are manifestations of vulnerability, and are generally precipitated by these underlying

root causes and dynamic pressures. Using random effects panel data methods, we test the hypotheses implied by the model, and find general support for its predictions. We find that, generally speaking, wealthier countries are less vulnerable to climate disasters than poorer countries. But while wealthier countries are typically less vulnerable to climate disasters, countries with high income inequality are more vulnerable. Since income inequality is also likely indicative of an unequal distribution of social and political power and resources, a more unequal income distribution can contribute to the marginalization of segments of the population. Other factors that capture a degree of social marginalization, such as the dependency ratio and ethnic fractionalization, also suggest that countries with marginalized populations are more vulnerable to climate disasters. Finally, consistent with prevailing political economy theories, we find that more democratic countries are less vulnerable to climate related disasters.

References

- Abney, F. and L. Hill (1966). Natural disasters as a political variable: The effect of a hurricane on an urban election. *The American Political Science Review* 60(4), 974–981.
- Adger, W. (1996). Approaches to vulnerability to climate change. Global Environmental Change Working Paper 96-05, Centre for Social and Economic Research on the Global Environment (CSERGE), University of East Anglia and University College, London.
- Adger, W. (1999). Social vulnerability to climate change and extremes in coastal Vietnam. *World Development* 27(2), 249–269.
- Alesina, A., A. Devleeschauwer, W. Easterly, S. Kurlat, and R. Wacziarg (2003). Fractionalization. *Journal of Economic Growth* 8(2), 155–194.
- Allan, R. and B. Soden (2008). Atmospheric warming and the amplification of precipitation extremes. *Science* 321(5895), 1481.
- Asiedu, E. (2002). On the determinants of foreign direct investment to developing countries: is Africa different? *World Development* 30(1), 107–119.
- Baltagi, B. (2001). *Econometric Analysis of Panel Data*. New York: John Wiley & Sons, Ltd.
- Battisti, D. and R. Naylor (2009). Historical warnings of future food insecurity with unprecedented seasonal heat. *Science* 323(2), 240–244.
- Ben-David, D. (1993). Equalizing exchange: trade liberalization and income convergence. *The Quarterly Journal of Economics* 108(3), 653–679.
- Besley, T. and R. Burgess (2002). The political economy of government responsiveness: Theory and evidence from india*. *Quarterly Journal of Economics* 117(4), 1415–1451.
- Blaikie, P., T. Cannon, I. Davis, and B. Wisner (1994). *At Risk: Natural hazards, people’s vulnerability, and disasters*. Routledge.
- Bommer, J. (1985). The politics of disaster–Nicaragua. *Disasters* 9(4), 270–278.

- Chambers, R. (1997). *Whose reality counts? Putting the first last*. London: Intermediate Technology Publications.
- Cohen, C. and E. Werker (2008). The Political Economy of “Natural” Disasters. *Journal of Conflict Resolution* 52(6), 795.
- Deininger, K. and L. Squire (1996). A new data set measuring income inequality. *The World Bank Economic Review* 10(3), 565–591.
- Devereux, S. (1993). *Theories of famine*. New York: Harvester Wheatsheaf.
- Diffenbaugh, N., J. Pal, F. Giorgi, and X. Gao (2007). Heat stress intensification in the Mediterranean climate change hotspot. *Geophysical Research Letters* 34(11), Available online at: <http://www.agu.org/journals/gl/gl10711/2007GL030000/2007GL030000.pdf>.
- Diffenbaugh, N., J. Pal, R. Trapp, and F. Giorgi (2005). Fine-scale processes regulate the response of extreme events to global climate change. *Proceedings of the National Academy of Sciences* 102(44), 15774–15778.
- Dollar, D. (1992). Outward-oriented developing economies really do grow more rapidly: evidence from 95 LDCs, 1976-1985. *Economic Development and Cultural Change* 40(3), 523–544.
- Emanuel, K. (2005). Increasing destructiveness of tropical cyclones over the past 30 years. *Nature* 436(7051), 686–688.
- Frankel, J. and D. Romer (1999). Does trade cause growth? *American Economic Review* 89(3), 379–399.
- Gassebner, M., A. Keck, and R. Teh (2010). Shaken, not stirred: the impact of disasters on international trade. *Review of International Economics* 18(2), 351–368.
- Guha-Sapir, D., D. Hargitt, and P. Hoyois (2004). *Thirty Years of Natural Disasters 1974-2003: The Numbers*. Louvain-la-Neuve: Presses univ. de Louvain.

- Guimaraes, P., F. L. Hefner, and D. P. Woodward (1992). Wealth and Income Effects of Natural Disasters: An Econometric Analysis of Hurricane Hugo. *Review of Regional Studies* 23, 97–114. Presented at the 1992 Meetings of the Southern Regional Science Association.
- Heston, A., R. Summers, and B. Aten (2009). *Penn World Table, Version 6.3*. Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania.
- Hewitt, K. (1983). The idea of calamity in a technocratic age. In K. Hewitt (Ed.), *Interpretations of Calamity from the Viewpoint of Human Ecology*, pp. 3–32. Boston: Allen & Unwin.
- Kahn, M. (2005). The death toll from natural disasters: the role of income, geography, and institutions. *Review of Economics and Statistics* 87(2), 271–284.
- Kellenberg, D. and A. Mobarak (2008). Does rising income increase or decrease damage risk from natural disasters? *Journal of Urban Economics* 63(3), 788–802.
- Khandker, S. (2007). Coping with flood: role of institutions in Bangladesh. *Agricultural Economics* 36(2), 169–180.
- Loree, D. and S. Guisinger (1995). Policy and non-policy determinants of US equity foreign direct investment. *Journal of International Business Studies* 26(2), 281–299.
- Mendelsohn, R., A. Dinar, and L. Williams (2006). The distributional impact of climate change on rich and poor countries. *Environment and Development Economics* 11(02), 159–178.
- Millennium Ecosystem Assessment (2005). *Ecosystems and Human Well-Being: Synthesis Report*. Washington, D.C.: World Resources Institute.
- Min, S., X. Zhang, F. Zwiers, and G. Hegerl (2011). Human contribution to more-intense precipitation extremes. *Nature* 470(7334), 378–381.
- Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development Economics* 88, 221–231.
- Noy, I. and A. Nualsri (2011). Fiscal storms: public spending and revenues in the aftermath of natural disasters. *Environment and Development Economics* 16, 113–128.

- Noy, I. and T. B. Vu (2010). The Economics of Natural Disasters in a Developing Country: The Case of Vietnam. *Journal of Asian Economics* 21, 345–354.
- Pall, P., T. Aina, D. Stone, P. Stott, T. Nozawa, A. Hilberts, D. Lohmann, and M. Allen (2011). Anthropogenic greenhouse gas contribution to flood risk in England and Wales in autumn 2000. *Nature* 470(7334), 382–385.
- Parry, M., O. Canzaiani, J. Palutikof, P. Van der Linden, and C. Hanson (2007). *Climate Change 2007: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge: Cambridge Univ. Press.
- Parry, M., O. Canziani, J. Palutikof, and Co-Authors (2007). Technical Summary. In M. Parry, O. Canziani, J. Palutikof, P. van der Linden, and C. Hanson (Eds.), *Climate Change 2007: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge: Cambridge Univ Pr.
- Quazi, R. (2007). Economic freedom and foreign direct investment in East Asia. *Journal of the Asia Pacific Economy* 12(3), 329–344.
- Rodriguez, F. and D. Rodrik (2001). Trade policy and economic growth: a skeptic’s guide to the cross-national evidence. In B. Bernanke and K. S. Rogoff (Eds.), *Macroeconomics Annual 2000*, Volume 15, pp. 261–325. Cambridge, MA: MIT Press.
- Sachs, J. and A. Warner (1995). Economic reform and the process of global integration. *Brookings Papers on Economic Activity* 1995(1), 1–118.
- Schelling, T. (1992). Some economics of global warming. *The American Economic Review* 82(1), 1–14.
- Sen, A. (1981). *Poverty and famines*. Oxford: Oxford University Press.
- Sen, A. (1999). *Development as freedom*. Oxford: Oxford University Press.

- Shaughnessy, T., M. White, and M. Brendler (2010). The Income Distribution Effect of Natural Disasters: An Analysis of Hurricane Katrina. *Regional Analysis & Policy* 40(1), 84–95.
- Skidmore, M. and H. Toya (2002). Do natural disasters promote long-run growth? *Economic Inquiry* 40(4), 664–687.
- Strömberg, D. (2007). Natural disasters, economic development, and humanitarian aid. *The Journal of Economic Perspectives* 21(3), 199–222.
- Tol, R., T. Downing, O. Kuik, and J. Smith (2004). Distributional aspects of climate change impacts. *Global Environmental Change* 14(3), 259–272.
- Toya, H. and M. Skidmore (2007). Economic development and the impacts of natural disasters. *Economics Letters* 94, 20–25.
- Trapp, R., N. Diffenbaugh, H. Brooks, M. Baldwin, E. Robinson, and J. Pal (2007). Changes in severe thunderstorm environment frequency during the 21st century caused by anthropogenically enhanced global radiative forcing. *Proceedings of the National Academy of Sciences* 104(50), 19719.
- Webster, P., G. Holland, J. Curry, and H. Chang (2005). Changes in tropical cyclone number, duration, and intensity in a warming environment. *Science* 309(5742), 1844–1846.
- Wheeler, D. (2011). Quantifying Vulnerability to Climate Change: Implications for Adaptation Assistance. Working Paper 240, Center for Global Development.
- World Development Report (2010). *World Development Report 2010: Development and Climate Change*. The World Bank.

Table 1: Numbers of Climate-Related Deaths and Affected Persons by Decade, 1940-2009 (,000s)

		1940-49	1950-59	1960-69	1970-79	1980-89	1990-99	2000-09
Deaths	Droughts	3,450	0	1,511	119	554	3	1
	Extreme Temperatures	0	1	1	2	5	9	91
	Floods	101	2,062	32	51	52	95	54
	Mass Movements (wet)	18	2	5	7	6	8	6
	Storms	127	35	134	357	47	211	172
Affected	Droughts	0	0	117,900	263,707	592,746	309,914	754,897
	Extreme Temperatures	0	0	0	1	40	7,135	85,404
	Floods	2	13,178	42,375	207,877	468,401	1,436,605	948,508
	Mass Movements (wet)	0	6	4,002	97	3,526	2,035	1,513
	Storms	2,534	6,167	30,245	52,540	141,405	224,071	397,201

Source: EM-DAT: The OFDA/CRED International Disaster Database - www.emdat.be -
 Université Catholique de Louvain - Brussels - Belgium

Table 2: Numbers of Climate-Related Disasters by Decade, 1940-2009

	1940-49	1950-59	1960-69	1970-79	1980-89	1990-99	2000-09
Droughts	13	0	48	65	126	137	174
Extreme Temperatures	0	8	9	15	38	92	221
Floods	11	81	155	263	524	865	1,728
Mass Movements (wet)	4	20	24	53	101	145	150
Storms	53	120	212	291	559	899	1,054

Source: EM-DAT: The OFDA/CRED International Disaster Database - www.emdat.be -
 Université Catholique de Louvain - Brussels - Belgium

Table 3: Probability of Experiencing Various Climate-Related Disasters—Random Effects Panel Probit Estimation

	(1) Any Disaster	(2) Drought	(3) Extreme Temperature	(4) Flood	(5) Wet Mass Movement	(6) Storm	(7) Any Disaster
ln(Real Per Capita GDP)	0.021 (0.191)	-0.313*** (-3.089)	0.188 (1.350)	0.020 (0.230)	0.123 (1.013)	-0.104 (-0.764)	-0.227 (-1.459)
Polity	-0.017 (-0.860)	0.002 (0.081)	-0.007 (-0.236)	-0.033* (-1.890)	0.041* (1.709)	0.011 (0.528)	-0.019 (-1.013)
Political Rights	0.007 (0.108)	0.019 (0.254)	0.062 (0.663)	0.097* (1.664)	-0.007 (-0.088)	-0.024 (-0.331)	0.009 (0.136)
Elevation	0.310* (1.804)	0.191 (1.428)	-0.271 (-1.306)	0.153 (1.136)	0.763*** (4.111)	0.033 (0.145)	0.340** (2.048)
Abs. Value of Latitude	-0.006 (-0.510)	-0.000 (-0.020)	-0.001 (-0.097)	-0.021** (-2.412)	-0.036*** (-3.026)	0.027** (1.974)	-0.011 (-0.981)
Area Near Ice-Free Coast	0.823** (2.170)	0.570 (1.619)	-0.299 (-0.637)	0.071 (0.233)	0.084 (0.197)	0.994** (2.128)	0.811** (2.227)
ln(Land Area)	0.396*** (5.328)	0.135** (2.233)	0.333*** (3.807)	0.380*** (6.400)	0.379*** (4.569)	0.244*** (2.707)	0.419*** (5.750)
Time Trend	0.077*** (8.607)	0.007 (0.660)	0.061*** (4.697)	0.061*** (7.773)	0.011 (1.068)	0.037*** (4.207)	0.079*** (8.799)
ln(Real Per Capita GDP)× High							0.190** (2.373)
ln(Real Per Capita GDP)× Middle							0.082 (1.531)
Constant	-2.689*** (-4.150)	0.345 (0.560)	-5.573*** (-6.496)	-2.293*** (-4.498)	-3.592*** (-4.944)	-2.684*** (-3.644)	-1.368 (-1.612)
# Obs	1055	932	1023	1055	1041	1055	1055
# Groups	103	89	99	103	101	103	103
Log-Likelihood	-490.490	-231.395	-177.694	-511.666	-241.740	-413.400	-487.596

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Z-statistics in parentheses. Each of these regressions contain time-invariant regional dummy variables to control for geographic heterogeneity. There are no Caribbean country-year observations in our sample for which a drought or an extreme temperature disaster was reported. Inclusion of a Caribbean regional dummy would perfectly predict a 0 entry for the binary dependent variable in the regressions reported in columns (2) and (3). Observations for Caribbean countries were dropped from the sample prior to estimating these models. Similarly, there are no North American country-year observations in our sample for which a drought or a wet mass movement disasters was reported. North American countries were dropped from the sample prior to estimating the models in column (2) and (5), respectively. Finally, there were no Other European country-year observations in our sample for which a drought was reported. These observations were dropped from the sample prior to estimating the model in column (2). These changes to the sample size are reflected in the number of observations and the number of groups for these models.

Table 4: Probability of Experiencing a Large Number of Deaths or Affected Persons—Random Effects Panel Probit Estimation

	(1) Large Number Affected	(2) Large Number Killed
ln(Real Per Capita GDP)	-0.660*** (-4.928)	-0.286** (-2.503)
Elevation	0.066 (0.264)	0.734*** (3.090)
Abs. Value of Latitude	0.014 (1.201)	0.012 (1.237)
ln(Land Area)	0.424*** (3.920)	0.435*** (4.583)
Area Near Ice-Free Coast	1.199** (2.224)	1.823*** (3.908)
Polity	-0.009 (-0.373)	0.000 (0.020)
Political Rights	0.077 (0.878)	0.029 (0.358)
Time Trend	0.019 (1.578)	0.003 (0.265)
Constant	1.755** (2.113)	-0.804 (-1.086)
# Obs	1055	1055
# Groups	103	103
Log-Likelihood	-239.800	-264.156

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Z-statistics in parentheses. For these regressions, we were forced to omit the regional dummy variables, since for each of the catastrophic outcomes there were several regions for which one of the binary outcomes were perfectly predicted by the regional dummies.

Figure 1: Average Predicted Probability of Experiencing a Climate-Related Disaster and Average Number of Deaths

Note: Contour lines represent the two-dimensional density contours from nonparametric kernel density estimation of the joint distribution using an axis-aligned bivariate normal kernel.

Figure 2: Average Predicted Probability of Experiencing a Climate-Related Disaster and Average Number of Persons Affected

Note: Contour lines represent the two-dimensional density contours from nonparametric kernel density estimation of the joint distribution using an axis-aligned bivariate normal kernel.

Figure 3: Average Rate of Climate-Related Deaths and Average Real Per Capita GDP

Note: Contour lines represent the two-dimensional density contours from nonparametric kernel density estimation of the joint distribution using an axis-aligned bivariate normal kernel.

Figure 4: Average Rate of Persons Affected by Climate-Related Disasters and Average Real Per Capita GDP

Note: Contour lines represent the two-dimensional density contours from nonparametric kernel density estimation of the joint distribution using an axis-aligned bivariate normal kernel.

Table 5: Test of Pressure and Release Model—Random Effects Panel Regression

	Unsafe Conditions		Dynamic Pressures		Root Causes		Full Pressure and Release Model	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\ln\left(\frac{\text{Deaths}}{\text{Pop}}\right)$	$\ln\left(\frac{\text{Affected}}{\text{Pop}}\right)$	$\ln\left(\frac{\text{Deaths}}{\text{Pop}}\right)$	$\ln\left(\frac{\text{Affected}}{\text{Pop}}\right)$	$\ln\left(\frac{\text{Deaths}}{\text{Pop}}\right)$	$\ln\left(\frac{\text{Affected}}{\text{Pop}}\right)$	$\ln\left(\frac{\text{Deaths}}{\text{Pop}}\right)$	$\ln\left(\frac{\text{Affected}}{\text{Pop}}\right)$
ln(Real Per Capita GDP)	-0.160 (-0.866)	-0.706** (-2.373)					-0.178 (-0.897)	-0.695** (-2.146)
ln(Telephones per 1,000 people)	0.176 (1.312)	-0.186 (-0.561)					0.051 (0.346)	-0.267 (-0.676)
ln(Dependency Ratio)	2.153*** (3.022)	0.603 (0.397)					1.603** (2.395)	0.239 (0.156)
ln(Physicians per 1,000 people)	-0.035 (-0.404)	-0.373*** (-2.597)					-0.012 (-0.120)	-0.383** (-2.191)
Ethnic Fractionalization	-0.667 (-1.117)	-3.531*** (-3.818)					-0.371 (-0.613)	-3.326*** (-3.507)
ln(Population Growth)			-0.000 (-0.003)	-0.084 (-0.363)			0.048 (0.632)	-0.074 (-0.312)
ln(Population Density)			0.143 (1.277)	-0.244 (-1.173)			0.199 (1.492)	-0.166 (-0.961)
Polity					-0.024 (-0.966)	-0.090 (-1.576)	-0.017 (-0.668)	-0.062 (-1.320)
Political Rights					0.099 (1.028)	0.166 (0.860)	0.109 (1.023)	0.241 (1.299)
Openness to Trade					0.005** (2.000)	0.013** (2.316)	0.006** (2.405)	0.012** (2.413)
Avg. Gini Coefficient					0.032** (2.331)	-0.004 (-0.149)	0.026* (1.953)	-0.010 (-0.412)
Time Trend	-0.020 (-1.298)	0.065** (2.340)	-0.036*** (-3.393)	0.023 (0.972)	-0.037*** (-2.828)	0.018 (0.658)	-0.026 (-1.620)	0.060* (1.891)
Constant	-14.755*** (-3.808)	0.596 (0.079)	-6.413*** (-11.398)	-0.421 (-0.386)	-7.897*** (-8.852)	-1.573 (-0.950)	-14.796*** (-3.925)	2.194 (0.301)
# Obs	577	577	577	577	577	577	577	577
# Groups	95	95	95	95	95	95	95	95
R ² : Within	0.11	0.12	0.10	0.12	0.09	0.11	0.10	0.12
R ² : Between	0.17	0.68	0.17	0.59	0.23	0.65	0.27	0.73
R ² : Overall	0.19	0.44	0.16	0.40	0.19	0.41	0.22	0.45

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Z-statistics in parentheses. For each regression, the dependent variable is computed per 1,000 people in the population. Each of these regressions contain variables to control for the number of droughts, extreme temperature disasters, floods, wet mass movements, and storms experienced in a country-year observation, as well as time-invariant regional dummy variables. Estimates have been obtained using the Swamy-Arora method for estimating variance components in unbalanced panels. Standard errors have been adjusted to control for within-country clustering and serial correlation as well as cross-sectional heteroskedasticity.

A Summary of Data Sources

Table A.1: Summary of Data Sources

Variable	Description	Source
Deaths	Number of persons killed by climate disasters	EM-DAT
Affected	Number of persons injured, displaced, or otherwise needing immediate attention resulting from climate disasters	EM-DAT
Disasters	Number of disasters (by type)	EM-DAT
Elevation	Elevation (meters above sea level), country average	Center for International Development
Latitude	Latitude (degrees N), country geographic centroid	Center for International Development
Area Near Ice-Free Coast	Land area within 100 km. of ice-free coast (% of total land area)	Center for International Development
Land Area	Total land area (sq. km)	World Development Indicators
Real Per Capita GDP	GDP per capita (constant 2000 US\$)	World Development Indicators
Telephones per 1,000 people	Fixed telephone lines per 1,000 people in the population	World Development Indicators
Physicians per 1,000 people	Number of physicians per 1,000 people in the population	World Development Indicators
Dependency Ratio	Age dependency ratio; ratio of dependents (younger than 15 or older than 64) to the working age population (% of working age population)	World Development Indicators
Population Growth	Growth rate of the national population (%)	World Development Indicators
Population Density	People per sq. km of land area	World Development Indicators
Ethnic Fractionalization Index	Index of fractionalization (0–1, where 0 is perfectly homogenous and 1 is perfectly heterogeneous)	Alesina et al. (2003)
Polity Measure	Quality of political institutions (0–20, where 20 is most democratic)	Polity IV
Political Rights	Index of political rights (1–7, reformulated to where 7 is indicative of greatest amount of rights)	Freedom House, “Freedom in the World”
Openness to Trade	Exports plus imports as a share of real GDP	Penn World Tables, v. 6.3 (Heston et al., 2009)
Gini Coefficient	Gini coefficient of income inequality	World Bank “Measuring Income Inequality Database”