THE DEATH TOLL FROM NATURAL DISASTERS: THE ROLE OF INCOME, GEOGRAPHY, AND INSTITUTIONS

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Abstract—Using a new data set on annual deaths from disasters in 73 nations from 1980 to 2002, this paper tests several hypotheses concerning natural-disaster mitigation. Though richer nations do not experience fewer natural disasters than poorer nations, richer nations do suffer less death from disaster. Economic development provides implicit insurance against nature's shocks. Democracies and nations with higher-quality institutions suffer less death from natural disaster. Because climate change is expected to increase the frequency of natural disasters such as floods, these results have implications for the incidence of global warming.

I. Introduction

BETWEEN 1980 and 2002, India experienced fourteen major earthquakes that killed a total of 32,117 people while the United States experienced eighteen major earthquakes that killed only 143 people. A disproportionate share of the deaths caused by such environmental shocks as earthquakes, floods, cyclones, hurricanes, and extreme temperature events are borne by people in developing countries. The Intergovernmental Panel on Climate Change (2001) reports that 65% of world deaths from natural disasters between 1985 and 1999 took place in nations whose incomes were below $760 per capita.[1]

Using a new data set on annual deaths from natural disasters in 73 nations from 1980 to 2002, this paper tests four hypotheses. First, do richer nations experience fewer natural-disaster shocks? Second, when natural disasters take place, how many fewer fatalities do they cause in richer nations than in poorer nations? Third, what role does national geography play in determining the death toll from natural disasters? Fourth, controlling for other national attributes, do institutions matter in mitigating the consequences of natural disasters?

Determining the relative importance of income, geography, and institutions in insulating nations from nature's shocks is important for three reasons. First, if richer nations are sufficiently insulated from nature's shocks relative to poorer countries, then this finding contributes to cross-national living-standards comparisons. Second, the comparative economics literature has attempted to measure the quantitative importance of "good institutions" in explaining differences in cross-national economic performance (Acemoglu, Johnson, & Robinson, 2001, 2002; Easterly & Levine, 2002; Rodrik, Subramanian, & Trebbi 2002). Death from natural disaster offers a new outcome measure for testing hypotheses. Finally, many environmentalists care about the equity consequences of global warming. Scientists have predicted that global warming will accelerate the count of floods. It is important to have estimates of what is the human toll caused by such events and how these death counts differ across nations. The political economy of who supports costly climate change policy hinges on the expected benefits of mitigating climate change.

To preview the paper's results, national income plays little role in explaining which nations experience a natural disaster. But richer nations suffer less death from natural disaster. Geography and institutional quality also play an important role in explaining cross-national patterns. Nations in Asia and the Americas suffer more deaths from natural disaster than nations in Africa. Democracies and nations with less income inequality suffer fewer deaths from disasters. Ordinary least squares (OLS) and instrumental variables (IV) estimates indicate that a host of institutional quality measures are negatively correlated with national-disaster death counts.

The paper's next section presents the data sources used in the empirical analysis. Section III examines which nations experience the most natural shocks. Section IV presents the empirical framework and the main results concerning deaths from disaster.

II. Data

The raw data on deaths from natural disasters come from the Centre for Research on the Epidemiology of Disasters (CRED) (see International Federation of Red Cross, 2002). Since 1988, CRED has maintained the Emergency Events Database (EM-DAT), accessible at http://www.cred.be/emdat/. This Web page provides the rationale for why the data set has been collected:

> In recent years, natural and man-made disasters have been affecting increasing numbers of people throughout the world. Budgets for emergency and humanitarian aid have skyrocketed. Efforts to establish better preparedness for and prevention of disasters have been a priority concern of donor agencies, implementing agencies and affected countries. For this reason, demand for complete and verified data on disasters and their human and economic impact, by country and type of disaster has been growing. . . . The database is compiled from various sources, including UN agencies,

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[1] "Ninety percent of the disaster victims worldwide live in developing countries where poverty and population pressures force growing numbers of poor people to live in harm's way on flood plains, in earthquake prone zones and on unstable hillsides. Unsafe buildings compound the risks. The vulnerability of those living in risk prone areas is perhaps the single most important cause of disaster casualties and damage" (Secretary General of the United Nations Kofi Annan, 1999).

TABLE 1.—NATURAL-DISASTER STATISTICS FOR SAMPLE NATIONS

Country	Annual Average Total Count of Disasters	Annual Average Total Deaths per Million People	Average Deaths per Earthquake	Average Deaths per Extreme Temperature Event	Average Deaths per Flood	Average Deaths per Landslide	Average Deaths per Windstorm
Algeria	1.3478	7.1542	320.1111		66.8421	15.0000	2.0000
Argentina	2.0000	0.4238	3.0000	7.2500	7.9667	.	4.7000
Australia	4.0000	0.6741	7.6667	5.7500	3.5926	14.0000	1.6964
Austria	1.0435	0.7453	.	0.0000	3.7143	23.2500	1.2500
Bangladesh	6.2609	65.9391	6.0000	139.6667	211.4565	.	1,940.4940
Belgium	1.0000	0.0521	1.0000	0.0000	0.9000	.	0.1000
Bolivia	1.0556	4.3244	46.0000	7.5000	28.3158	37.2500	4.0000
Brazil	3.3913	0.8721	1.0000	28.0000	42.7400	42.8000	14.2222
Cambodia	0.5714	7.4703	.	.	143.0000	.	.
Canada	1.1304	0.1839	.	0.0000	2.6667	.	7.1687
Chile	1.5217	3.6315	40.0000	0.6667	34.5882	86.5000	18.6250
China	13.9130	1.7657	36.9039	29.1429	328.4300	63.9091	71.7268
Colombia	2.9130	5.4748	162.5455	.	34.5484	76.5714	9.0000
Costa Rica	1.0000	2.7530	7.5714	.	4.0909	7.0000	22.5000
Cuba	1.6667	0.7885	0.0000	.	7.3333	.	1.8571
Denmark	0.3913	0.1591	.	0.0000	.	.	2.3750
Dominican Republic	0.6957	2.8905	.	.	9.3750	.	50.3750
Ecuador	1.1739	7.7614	43.1250	.	60.2500	114.8571	.
Egypt	0.6087	1.0882	190.3333	19.0000	125.2000	34.0000	24.0000
El Salvador	0.8696	27.4940	569.7500	.	62.4444	22.0000	98.4000
Ethiopia	1.7692	0.7672	.	.	27.1500	13.0000	.
Fiji	0.8333	9.3557	0.0000	.	14.5000	.	9.4211
France	3.4348	0.3699	.	8.0000	4.4839	9.1429	6.9714
Germany	0.7391	0.0674	1.0000	30.0000	6.0000	.	6.3750
Ghana	0.4615	0.9618	.	.	36.3333	.	.
Greece	1.5217	6.0054	14.0588	216.8000	3.6000	.	16.6667
Guatemala	1.0870	6.6072	5.8750	0.0000	80.3000	47.3333	130.6667
Haiti	1.1053	15.8560	.	.	15.7857	0.0000	284.3333
Honduras	1.0000	132.7648	1.0000	.	43.6000	10.0000	2,953.8000
Hong Kong	1.4783	1.5246	.	10.0000	3.6000	1.0000	7.2727
Hungary	0.4348	0.5624	.	81.0000	1.2857	.	22.0000
India	10.0870	4.7195	2294.0720	328.7692	291.7245	91.1429	332.0606
Indonesia	5.7826	1.9380	92.5455	.	46.3939	47.5000	0.6667
Iran	4.3043	41.2894	1105.3260	.	69.0625	26.5000	39.0000
Ireland	0.5217	0.4608	.	.	1.0000	.	3.8889
Italy	2.0870	3.9857	299.3750	3.3333	17.5294	15.2500	8.2500
Jamaica	0.6087	2.6586	.	.	12.8333	.	8.8750
Japan	4.0000	2.7159	311.0000	.	46.1429	26.6364	17.7500
Kenya	0.5217	0.7109	0.0000	.	36.3333	16.0000	50.0000
Korea, Republic	2.0435	2.9153	.	33.5000	65.6111	22.0000	64.3600
Madagascar	0.8696	3.7580	.	.	0.0000	.	58.2222
Malawi	0.9286	4.2386	9.0000	.	46.4167	.	.
Malaysia	0.8696	1.2154	.	.	7.5385	38.0000	90.6667
Mexico	4.2609	6.9996	528.1765	90.1667	62.4231	24.6667	42.6000
Morocco	0.8462	2.7069	.	0.0000	103.0000	.	14.0000
Mozambique	0.8261	4.3834	.	.	94.7000	87.0000	58.3750
Nepal	1.6522	14.0229	404.5000	30.0000	220.3684	113.3333	16.16667
New Zealand	1.3913	0.2120	1.0000	0.0000	0.2500	.	1.6667
Nicaragua	0.7826	41.8757	62.0000	.	8.8333	.	403.3333
Nigeria	1.5333	0.4064	.	39.0000	27.4118	10.6667	100.0000
Pakistan	3.2609	3.1358	46.9333	91.2222	187.4074	33.3333	76.6667
Panama	0.5652	1.6756	30.0000	.	2.4444	.	14.0000
Papua New Guinea	0.8000	6.2280	10.6667	.	11.6000	104.6667	23.5000
Peru	2.9130	7.4365	23.6111	21.0000	74.0714	63.5000	59.0000
Philippines	8.4348	16.4698	253.2000	.	38.2000	63.1111	153.8512
Poland	1.0000	2.1226	.	134.1667	29.6667	.	3.5000
Portugal	0.3913	0.3544	.	0.0000	12.8333	.	2.0000
Romania	2.2727	1.0186	.	15.2500	8.5000	0.0000	7.2500
Russia	6.0000	2.8809	400.2000	107.4667	14.4815	56.7500	18.6364
South Africa	1.5652	1.7289	11.3333	30.0000	68.8235	34.0000	11.2857

TABLE 1.—(CONTINUED)

Country	Annual Average Total Count of Disasters	Annual Average Total Deaths per Million People	Average Deaths per Earthquake	Average Deaths per Extreme Temperature Event	Average Deaths per Flood	Average Deaths per Landslide	Average Deaths per Windstorm
Spain	1.3043	0.4931	0.0000	17.5000	16.0000	84.0000	8.5385
Sri Lanka	1.4348	1.6455	.	.	19.3667	65.0000	2.5000
Switzerland	1.2174	0.3064	.	0.0000	1.0000	9.3333	0.8333
Taiwan	1.1053	1.2368	13.0000	.	20.5000	14.0000	23.5294
Tajikistan	2.2857	3.9778	1.0000	.	12.8889	25.5000	0.0000
Tanzania	1.4615	1.2361	1.0000	.	33.2857	13.0000	4.0000
Thailand	2.4348	2.1485	.	.	55.7838	39.0000	35.2778
Turkey	2.4348	16.1699	908.8636	19.2500	27.1667	77.0000	8.3600
United Kingdom	1.8696	0.2013	0.0000	16.0000	0.7857	.	8.3600
United States	17.9565	1.3337	7.9444	115.8333	6.3820	.	17.2361
Venezuela	1.0435	66.6421	16.3333	.	2,015.7330	96.0000	54.0000
Vietnam	4.0000	11.6504	.	.	98.8333	110.5000	270.9091
Yemen	1.1667	2.9587	11.0000	.	47.2727	.	15.0000

A period indicates that the nation did not experience this type of natural disaster.

non-governmental organizations, insurance companies, research institutes and press agencies.

In the raw data, the unit of analysis is a disaster. The CRED uses specific criteria for determining whether an event is classified as a natural disaster. These include: ten or more people were killed; 100 or more people were affected, injured, or homeless; significant damage was incurred; a declaration of a state of emergency and/or an appeal for international assistance was made (http://www.cred.be/emdat/). I am unable to study disasters that are not recorded in the CRED data.[2]

The data set provides indicators of disaster type. I focus on five types of environmental disasters. Earthquakes are sudden breaks within the upper layers of the earth, sometimes breaking the surface, resulting in the vibration of the ground. For 90% of the earthquakes reported in the EM-DAT data, the earthquake's Richter scale reading (a measure of the energy released during the peak of an earthquake) is recorded. Below, I use this information as a measure of the quality of the shock.[3] Extreme temperature events are heat waves and cold waves. Floods are significant rises of the water level in a stream, lake, reservoir, or coastal region. Slides are avalanches and landslides. Windstorms are cyclones, hurricanes, storms, tornados, tropical storms, and typhoons and winter storms. I chose to exclude such rare events as tsunamis because there were only 19 of these disasters recorded across the whole world during the years 1980 to 2002. In the EM-DAT data, earthquakes account for 12% of the natural disasters shocks, 5% are extreme temperature events, 40% are floods, 7% are slides, and 37% are windstorms.

The 73 nations included in my study are listed in table 1. Major nations such as China, India, and the United States are included as well as smaller nations. Just over 90% of all deaths reported in the EM-DAT database for these five natural-disaster categories took place in these 73 nations, and 79.3% of all natural disasters registered in this database took place in them. Thus, I am confident that my sample contains the bulk of the shocks. I exclude nations in the EM-DAT data if a nation reported no natural disasters for three years in a row or if there were large numbers of zeros in the disaster death counts. For example, the EM-DAT data report that nobody died from a natural disaster in Bhutan or Guyana during the years 1980 to 1993.

Table 1 provides national summary statistics reporting the annual average count of natural disasters, annual total deaths per million people, and disaggregated average death counts by disaster type. Relative to their population size, Honduras, Venezuela, Nigeria, and Bangladesh suffer the most death from disaster. The table highlights the heterogeneity in deaths from disasters. For example, the correlation between average deaths from earthquakes and average deaths from windstorms is −0.02.

Table 2 reports the three biggest disasters by disaster type for the 73 nations. Iran suffered the most earthquake deaths in 1990, and Bangladesh suffered the most windstorm deaths in 1991. The bottom row of the table reports the top three death counts from industrial disasters, the Bhopal (India) disaster of 1984 causing the most death. Relative to earthquakes, floods, and windstorms, the industrial death counts are much lower. Across my sample, the average death count per earthquake was 332. In the United States, the average earthquake killed 10 people.

I use the EM-DAT data to test how death from natural disasters depends on a nation's geography, institutions, and

[2] In the U.S., politics plays a key role in determining when a "disaster" has taken place. Garrett and Sobel (2003) report that an area is more likely to be designated as a "disaster area" if it is represented by powerful congressmen or if the state's voters support the President.

[3] I fail to reject the hypothesis that there is no time trend with respect to the Richter scale readings for earthquakes. If in the early years of the EM-DAT data only severe earthquakes were recorded, then I would have expected to observe a negative trend with respect to earthquake intensity over time.

TABLE 2.—DEATH COUNT OF MAJOR DISASTERS FROM 1980 TO 2002

Disaster Type	Death Count		
Earthquake	40,000 in Iran in 1990	20,005 in India in 2001	17,980 in Turkey in 1999
Extreme temperature	2,541 in India in 1998	1,030 in India in 2002	1,000 in Greece in 1987
Flood	30,000 in Venezuela in 1999	6,200 in China in 1980	3,656 in China in 1998
Landslide	640 in Colombia in 1987	472 in Nepal in 2002	400 in India in 1995
Windstorm	138,866 in Bangladesh in 1991	14,600 in Honduras in 1998	10,000 in Bangladesh in 1985
Industrial	2,500 in India in 1984	1,082 in Nigeria in 1998	508 in Brazil in 1984

The table reports the top three disasters by category for the set of nations listed in table 1.

income. The explanatory variables are merged in by nation and year from several separate data sources. National data on annual population and on real GDP per capita (1996 dollars, based on the Laspeyres index) are from the Penn World Tables, version 6.1 (Heston, Summers, & Aten, 2002). The data are available through the year 2000.[4] National geography data and population density are from Gallup, Sachs, and Mellinger (1999). Institutional quality is proxied for using several data sets. The first data source is Polity 4 (http://www.bsos.umd.edu/cidcm/polity/index.html). I use the polity data to construct a democracy variable, which takes on the values 0–20 (where 20 is the highest) that represents a nation's general openness of political institutions.

The second set of institutional quality variables is heterogeneity measures. As discussed in Alesina, Baqir, and Easterly (1999) and Knack and Keefer (1997), in more heterogeneous communities the ability of government to supply productive public goods may suffer. The nation's Gini coefficient for income is from the World Bank (see http://www.worldbank.org/research/growth/dddeisqu.htm). For each nation, I average the Gini measure within the year and then use the first observation from 1975 until the present available in the data set. Within nations, Gini measures are very highly correlated across years. As a second measure of national heterogeneity, I use the ethnic fragmentation measure reported in Alesina et al. (2003). The final set of government institutional quality measures are from Kaufmann, Kraay, and Mastruzzi (2003). These indicators are based on several hundred variables measuring perceptions of governance drawn from 25 separate data sources constructed by 18 different organizations. I use their data from the year 1996. Within nations, the 1996 data are highly correlated with the 2002 data.

[4] Because the EM-DAT data continue to the year 2002, I use the year 2000 Penn World Tables data for the values in the years 2001 and 2002.

Recent comparative economics papers have used historical variables to instrument for institutional quality today. Following this literature, I use the settler mortality risk variable reported in Acemoglu et al. (2001). I can use their data for 36 former colonies in my data set.

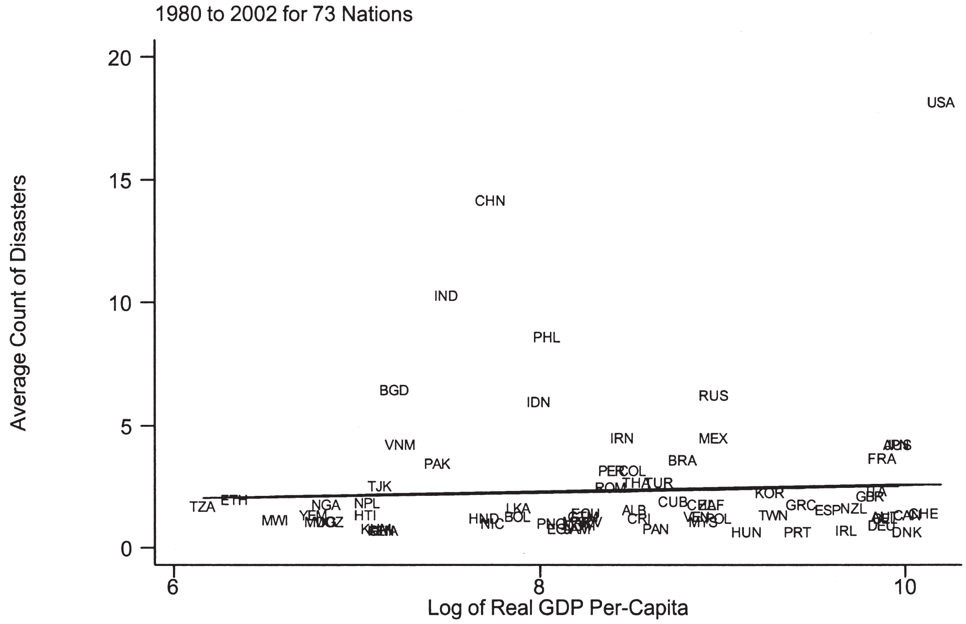
Table 3 reports the national summary statistics. Each year, the average nation experiences 2.4 natural disasters per year and suffers 376 deaths from natural disaster. Roughly half of these deaths are from windstorms. Floods and earthquakes also represent a large fraction of deaths; landslides and extreme temperature events cause relatively few deaths. My sample nations are roughly $1,000 richer than the average nation in the Penn World Tables sample ($\frac{1}{7}$ standard deviation higher), and the average population of the nations in my sample is twice as large as that in the Penn World Tables.

TABLE 3.—NATIONAL SUMMARY STATISTICS

Variable	Observations	Mean	Std. Dev.
Population (millions)	1,527	66.7039	173.8536
Elevation (1,000 m above sea level)	1,474	0.6647	0.5180
Absolute value of latitude (deg)	1,474	26.8225	16.5893
Average population density (1,000 persons/km^2)	1,474	776.6302	1,167.1470
Democracy	1,468	14.5456	6.3018
GDP per capita ($1,000)	1,527	8,244.3110	7,530.5130
Annual total count	1,527	2.3818	3.5823
Annual count of earthquakes	1,527	0.2783	0.7051
Annual count of extreme temperature events	1,527	0.1192	0.3902
Annual count of floods	1,527	0.9325	1.4262
Annual count of landslides	1,527	0.1827	0.5455
Annual count of windstorms	1,527	0.8690	2.1512
Annual total dead	1,527	375.9764	3,944.4270
Annual total dead from earthquakes	1,527	92.3864	1,304.4850
Annual total dead from extreme temperature	1,527	12.3870	100.8586
Annual total dead from floods	1,527	96.6477	836.6869
Annual total dead from landslides	1,527	10.4623	48.0147
Annual total dead from windstorms	1,527	164.0930	3,604.1390

The unit of observation is a nation-year covering the years 1980 to 2002.
Democracy takes on the values 0 to 20 with 20 being the highest democracy level.
Latitude is determined by the country's centroid. Average population density is the typical population density experienced by an individual.

FIGURE 1.—NATIONAL ANNUAL AVERAGE OF NATURAL-DISASTER COUNTS



III. What Types of Nations Suffer Natural Disasters?

The death toll from disasters could be higher in poor nations because they suffer more shocks or experience more death per shock. Figure 1 displays the cross-national relationship between each nation's average annual count of natural disasters and its per capita income. China and the United States stand out as two nations experiencing many shocks. The regression line presented in figure 1 is not downward sloping. In fact, it slopes slightly upward, indicating that richer nations do not experience fewer of these shocks.

To more fully examine what types of nations suffer natural disasters, I estimate probit models of the form

$$Prob(Disaster_{ijt}) = f(Geography_j, \\ Land\ Area_{jt}, GDP\ Per\ Capita_{jt}, Trend_t) \quad (1)$$

In equation (1), *Disaster* is a dummy variable that equals 1 if a natural disaster in category i took place in nation j in year t. The explanatory variables in these probits include national geography variables, the nation's per capita income level, and its land area. All else equal, larger nations should be more likely to experience a given shock.

Table 4 presents six estimates of equation (1). To ease the interpretation of the probit models, each column presents estimates of the marginal probabilities. Aggregating all disaster categories, an extra \$1,000 in GDP per capita has no effect on the probability that a natural disaster takes place. Looking across columns (2)–(5), we see that income has its largest effect in reducing the likelihood of a flood. An extra \$1,000 in GDP per capita lowers the probability of a flood taking place by 1 percentage point. Whether heavy rains lead to a flood depends on such factors as drainage capacity. Richer nations will have the resources to make such investments to preempt such events. The finding that richer nations are exposed to roughly the same number of natural shocks as poorer nations stands in contrast to a pure geographic theory of development that would state that certain areas are "cursed" by their physical location. Such a theory would posit that certain areas suffer from poor endowments, higher disease exposure, and more natural-disaster shocks.

Geography does matter in determining the distribution of natural-disaster shocks. Relative to Africa, Asia is 28 percentage points more likely to experience a natural disaster in any given year. Overall, specification (1) in the table shows that a nation's physical attributes (elevation and distance from the equator) do not have a statistically significant effect on disaster probabilities.

IV. The Role of Income, Geography, and Institutions in Minimizing Death Counts

This section uses two different data sets to estimate reduced-form equations to test for the importance of national income, geography, and institutions in mitigating the consequences of natural disasters.[5] The first data set's unit

[5] It would be a very challenging exercise to build a structural model of the choice of dying in a natural disaster. Unlike the choice of a new car, nobody chooses to die from a flood or an earthquake. Such an event is an unintended consequence of one's locational choice, government action, and bad luck. A structural approach would need to explicitly model each household's locational choice (that is, whether a household locates in a high-risk area or not) and each government's ability to provide quality infrastructure, regulations, and disaster relief that mitigate the death risk from natural disasters. The payoff of constructing a structural model of death from disaster would be that the research could attempt to recover population risk preferences and government efficiency at providing safety.

TABLE 4.—DETERMINANTS OF WHETHER A NATION EXPERIENCED A NATURAL DISASTER

Independent Variable	All (1)	Earthquakes (2)	Extreme Temperature (3)	Floods (4)	Landslides (5)	Windstorms (6)
America dummy	0.1715	0.1216	0.0995	0.1785	0.1199	0.1501
	(0.0442)	(0.0821)	(0.0516)	(0.0762)	(0.0426)	(0.0985)
Asia dummy	0.2849	0.2152	0.1140	0.3474	0.2447	0.3706
	(0.0403)	(0.1024)	(0.0686)	(0.0773)	(0.0588)	(0.1084)
Europe dummy	0.0192	0.1830	0.1540	0.0243	0.3621	−0.0936
	(0.0905)	(0.1767)	(0.0795)	(0.1179)	(0.1142)	(0.1263)
Elevation	0.0611	0.0975	−0.0270	0.0035	0.0882	−0.1008
	(0.0388)	(0.0447)	(0.0277)	(0.0401)	(0.0180)	(0.0545)
Absolute value of latitude	0.0040	−0.0009	0.0034	0.0030	−0.0040	0.0084
	(0.0024)	(0.0026)	(0.0014)	(0.0027)	(0.0012)	(0.0035)
Log land area	0.0610	0.0520	0.0360	0.0773	0.0467	0.0371
	(0.0116)	(0.0157)	(0.0087)	(0.0167)	(0.0081)	(0.0174)
GDP per capita ($1,000)	−0.0004	−0.0028	−0.0055	−0.0101	−0.0012	0.0045
	(0.0039)	(0.0040)	(0.0027)	(0.0045)	(0.0029)	(0.0056)
Time trend	0.0116	−0.0028	0.0059	0.0183	0.0035	0.0049
	(0.0023)	(0.0015)	(0.0015)	(0.0025)	(0.0010)	(0.0022)
Mean probability of event	0.7126	0.1861	0.0999	0.4990	0.1385	0.3363
Observations	1,451	1,451	1,451	1,451	1,451	1,451
Pseudo R^2	0.1344	0.122	0.2203	0.1358	0.1909	0.1301

The dependent variable is a dummy variable that equals 1 if a nation experiences a disaster in that category in a given year.

Each column in this table reports a separate probit model. Column (1) aggregates all five disaster categories, and columns (2–6) disaggregate the disasters by category. In column (2) the dependent variable equals 1 if at least one earthquake took place within a nation in a given year. The table reports marginal probabilities, and robust standard errors are reported in parentheses. The standard errors have been adjusted for clustering within nation. Africa is the omitted continent.

of analysis is an earthquake. I estimate the following equation using OLS:

$$\log(1 + Death_{ijt}) = Controls + b_1 \times \log(Per\ Capita\ GDP_{jt}) + b_2 \times Richter\ scale_{ijt} + U_{ijt}\,. \tag{2}$$

The data set is not a balanced panel. Some nations might experience multiple shocks in the same year while others experience none. If a nation in a given year does not experience a shock, it is not in the data set. Estimates of equation (2) allow me to study the role of income, geography, and institutions while holding the earthquake's severity constant. This allows for a test of whether national per capita income simply proxies for the good fortune of not being hit with severe shocks.

The second data set is a balanced panel. For each of the 73 nations during the years 1980 to 2002, I calculate total deaths from natural disasters.[6] As I will discuss below, I use this data set to compare OLS estimates with IV estimates. I also use the data to estimate count models. Annual national total death from natural disasters is a nonnegative count. A Poisson model is not used, due to the overdispersion of the death data. In 38% of the nation-year observations, total death from natural disasters equals 0. To take into account these observations, I estimate a zero-inflated negative binomial (ZINB) model where the log likelihood function L is defined by

$$L = \sum_{i \in S} \ln[F(z_i\gamma) + \{1 - F(z_i\gamma)\}p_i^m] + \sum_{i \notin S}[\ln\{1 - F(z_i\gamma)\}$$
$$+ \ln\Gamma(m + y_i) - \Gamma(y_i + 1) - \ln\Gamma(m) + m\ln p_i$$
$$+ y_i\ln(1 - p_i)\,,$$
$$m = 1/\alpha\,,$$
$$p_i = 1\sqrt{1 + \alpha\exp(x_i\beta)}\,,$$

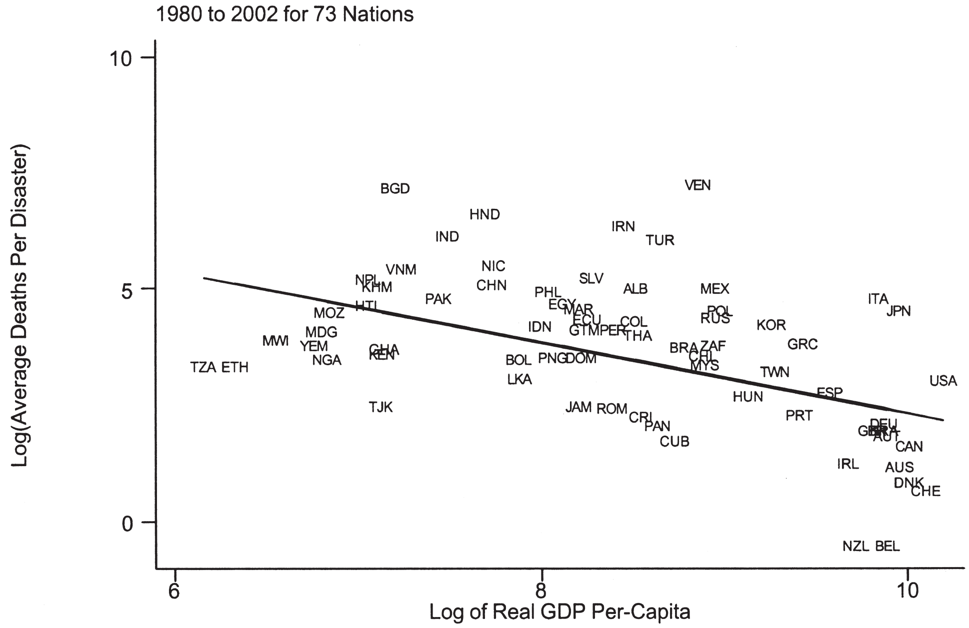
where F is the logit link, Γ is the gamma distribution, and S is the set of nation-year observations where nobody died from natural disaster.

The ZINB model allows for overdispersion in death counts by introducing a splitting process which models the outcomes as a zero or nonzero death count.[7] The zero-death-count model is estimated using a logit where the dependent variable equals 1 if nobody died from a natural disaster in nation j in year t. The logistic model includes as explanatory variables the count of natural disasters that a nation experiences in year t and the interaction of this count with the nation's population and income. A nation can only suffer death due to natural disaster if a natural disaster takes place. Interacting a nation's disaster count with the nation's population and income allows for the possibility that nations with smaller populations and higher incomes are less likely to suffer death from the disaster and a nation with a large population and low national income will suffer no death if

[6] For the ex-communist countries listed in table 1, I only use post-1990 data.

[7] For a recent application of this approach to studying the count of new plant openings across U.S. states see Keller and Levinson (2002).

FIGURE 2.—NATIONAL AVERAGE DEATHS PER NATIONAL DISASTER



no disasters take place. The likelihood of a nonzero death count for nation j in year t is modeled as a function of the number of shocks a nation experiences each year, national income, geography, and institutions and other national controls.

Neither of the empirical approaches presented in equations (2) and (3) includes nation fixed effects. To test how within-nation improvements in "good governance" and rising per capita incomes affect a nation's disaster death count would require both data that do not exist and economic adjustment that is unlikely to quickly take place. As discussed in Kaufman et al. (2003), it is quite difficult to create a within-nation governance database to test what are the benefits of improved national governance. Though rising national incomes can be measured, there is likely to be a long latency between economic development and improved average quality of infrastructure as new homes and new infrastructure are built of higher quality than the existing capital stock.

To organize this section's empirical findings, I report the results by major hypothesis, focusing on the role of income, geography, and institutions.

HYPOTHESIS 1: Richer nations suffer less death from disaster.

Richer people can self-protect through a number of strategies to reduce their natural-disaster risk exposure. Richer governments can provide implicit disaster insurance through effective regulation and planning and by providing quality infrastructure. After a disaster has struck, richer economies are able to provide high-quality emergency care to protect the population against death from disaster.

Within a nation some areas are more prone to natural disasters than others. Compensating differential theory predicts that land will be cheaper in areas at greater risk to experience a disaster. Hedonic real estate studies have documented this fact using data on earthquake zones (Brookshire et al., 1985; Willis & Asgary, 1997) and hurricanes (Hallstrom & Smith, 2003).[8] Richer people will demand homes located in safer communities and homes that are built out of stronger more durable materials. Once the shock has taken place, death counts can be higher if the nation does not have access to good medical care and emergency treatment and crisis management (Athey and Stern, 2002).

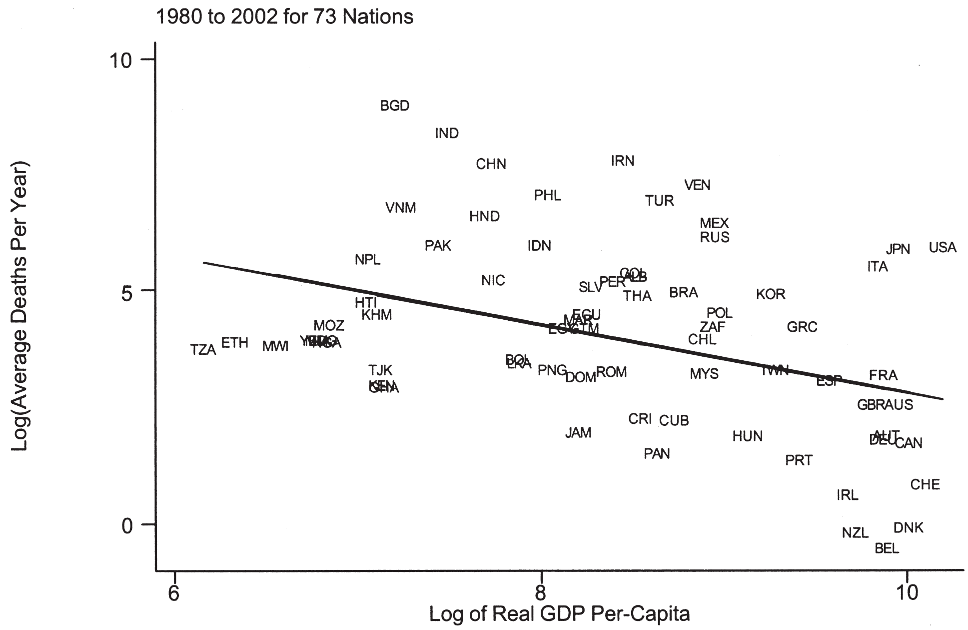
There are several pathways through which richer nations are insured against death from shocks. Richer nations will be able to invest in and enforce zoning and building codes. Building codes improve the structural soundness of a building, and this has a social value that the owner is unlikely to internalize, as it improves the quality of life of people in an immediate vicinity affected (Cohen & Noll, 1981).

For certain natural disasters such as hurricanes, richer nations have invested in computer modeling of storms. Spreading the resulting early warning information before the storm hits shore leads to mass evacuation, and this saves lives (Sheets & Williams, 2001). Based on a range of good-governance indicators, government quality rises as national income increases (La Porta et al., 1999). In this sense, good institutions and national income are positively correlated.

To begin to study the relationship between national income and deaths from disaster, I present two cross-national graphs. Figure 2 graphs national deaths from natural disaster

[8] Brookshire et al. (1985) estimate housing hedonic regressions and find that all else equal, homes in the earthquake-prone areas in Los Angeles sell at a 6% discount relative to other homes in Los Angeles.

FIGURE 3.—NATIONAL ANNUAL AVERAGE OF NATIONAL-DISASTER DEATHS



against national per capita income. A clear negative trend is observable, with nations such as Bangladesh and Venezuela standing out as outliers. Figure 3 graphs national average deaths per year and national per capita income. Again, the negative correlation is apparent.

Earthquakes are a major cause of death. To measure the insulating effects of income, in table 5 I use the earthquake sample and report estimates of equation (2). Controlling for national geography and population, column (1) shows that a 10% increase in per capita GDP decreases national earthquake deaths by 5.3%. As shown in column (3), this income elasticity is robust and does not change when I include the earthquake's Richter scale reading as an additional control. All else equal, more powerful earthquakes kill many more people. As shown in specification (2), it is not the case that richer countries experience less severe earthquakes. The results in tables 4 and 5 show that richer nations and poorer nations experience the same quantity and quality of natural shocks. In column (4), I drop the region fixed effects from the specification, and the estimated income elasticity grows by 50%. In column (5), I switch the dependent

TABLE 5.—DEATH AND DESTRUCTION CAUSED BY EARTHQUAKES

Dependent variable: Independent variable	(1) log(1 + *Death*)	(2) *Richter Scale*	(3) log(1 + *Death*)	(4) log(1 + *Death*)	(5) log(1 + *Injured*)
Richter scale			1.4859	1.4476	1.7084
			(0.2228)	(0.2245)	(0.1848)
Population density	−0.0977	0.2548	−0.4764	−0.4477	−0.2836
	(0.0869)	(0.0402)	(0.0975)	(0.1074)	(0.0886)
log(GDP per capita)	−0.5199	−0.0420	−0.4575	−0.6834	−0.4489
	(0.2359)	(0.1006)	(0.2211)	(0.2067)	(0.2440)
Time trend	0.0001	0.0043	−0.0064	0.0007	0.0258
	(0.0188)	(0.0074)	(0.0156)	(0.0148)	(0.0205)
Absolute value of latitude	0.0137	−0.0017	0.0162	0.0332	0.0181
	(0.0099)	(0.0044)	(0.0100)	(0.0082)	(0.0111)
Elevation	−0.4418	−0.1307	−0.2476	−0.5192	0.0367
	(0.3176)	(0.1364)	(0.2798)	(0.2363)	(0.2919)
Income Gini coefficient	0.0518	0.0103	0.0365	0.0307	0.0122
	(0.0134)	(0.0056)	(0.0143)	(0.0107)	(0.0145)
Ethnic fragmentation	−0.4372	−0.5780	0.4218	0.4890	−0.3101
	(0.6335)	(0.2725)	(0.6292)	(0.5811)	(0.6868)
Constant	4.9863	6.2069	−4.2366	−2.1730	−3.2132
	(2.0076)	(0.8689)	(1.9945)	(2.0064)	(2.1531)
Observations	340	362	340	323	340
Continent fixed effects	Yes	Yes	Yes	No	Yes
Adjusted R^2	0.0251	0.1456	0.2561	0.259	0.2966

Columns (1) and (3)–(5) report OLS estimates of equation (2) in the text. Robust standard errors are reported in parentheses. The standard errors are adjusted for within-nation correlation. The unit of analysis is an earthquake.

TABLE 6.—DETERMINANTS OF ANNUAL NATIONAL TOTAL DEATH FROM NATURAL DISASTER

	Zero-Inflated Negative Binomial Regressions			
Dependent Variable	(1)	(2)	(3)	(4)
Total count of disasters	0.0717	0.0460	0.0551	0.0320
	(0.0447)	(0.0385)	(0.0323)	(0.0358)
Log population	0.7325	0.8026	0.8376	0.8712
	(0.1843)	(0.1646)	(0.1418)	(0.1505)
GDP per capita	−0.1364	−0.1162	−0.0929	
	(0.0254)	(0.0224)	(0.0225)	
Income Gini coefficient		0.0908	0.1035	0.1170
		(0.0156)	(0.0162)	(0.0150)
Time trend	0.0232	0.0064	0.0170	0.0226
	(0.0271)	(0.0180)	(0.0198)	(0.0182)
America dummy		1.2217	0.8271	0.4486
		(0.4371)	(0.3987)	(0.3944)
Asia dummy		1.4425	0.9144	0.9519
		(0.3851)	(0.4447)	(0.4618)
Europe dummy		0.4174	0.1017	0.0270
		(0.4857)	(0.4524)	(0.5423)
Elevation		−0.6648	−0.2228	−0.1664
		(0.2314)	(0.2506)	(0.2280)
Absolute value of latitude		0.0339	0.0128	−0.0145
		(0.0170)	(0.0135)	(0.0113)
Average population density		−0.2239	−0.3050	−0.3841
		(0.0707)	(0.0748)	(0.0863)
Democracy			−0.0327	−0.0681
			(0.0247)	(0.0269)
Ethnic fragmentation			−2.5163	−2.8998
			(0.5488)	(0.6085)
Constant	−1.5025	−7.2349	−6.3756	−6.4018
	(1.7851)	(1.8991)	(1.7297)	(1.7726)
Zero-inflated logit model	−17.2394	−17.4259	−17.1748	−20.8597
	(2.3733)	(2.0679)	(2.9829)	
Total count of disasters	−17.2394	−17.4259	−0.6162	−0.5511
	(2.3733)	(2.0679)	(0.2324)	(0.2694)
Total count of disasters × log(population)	−0.6917	−0.6187	0.0826	
	(0.2596)	(0.2273)	(0.0340)	
Total count of disasters × GDP per capita	0.1035	0.0986	20.5509	24.1524
	(0.0397)	(0.0339)	(0.1976)	(2.5071)
Constant	20.9530	20.7333	0.9673	1.0258
	(0.7220)	(0.2263)	(0.0345)	(0.0322)
Ln α	1.1524	1.0141	2.6308	2.7894
	(0.0281)	(0.0308)	(0.0907)	(0.0897)
α	3.1659	2.7568	2.5875	
	(0.0890)	(0.0849)	(0.0972)	
Observations	1438	1438	1428	1428
Nonzero observations	885	885	880	880
Log likelihood function	−5,839.6	−5,763.2	−5,696.7	−5,729.5

Each column of this table reports a separate estimate of a zero-inflated negative binomial (ZINB) model. As presented in equation (3) in the text, the ZINB model has two equations. The lower panel of the table reports the logit model estimates of the probability that nobody in a given nation in a given year died from a natural disaster. The upper panel reports the results from the negative binomial regression. Standard errors are presented in parentheses. The standard errors are adjusted for within-nation clustering. The omitted category is African nations.

variable from deaths to the count of injured. The income elasticity is very similar to the one presented in column (3).

To study the effects of income on total national disaster death counts in more detail, I now report estimates from four ZINB models based on equation (3). These models are estimated using the balanced panel from 1980 to 2002 for the 73 nations listed in table 1. In table 6, column (1), I estimate the ZINB model while excluding variables that measure geography and institutional quality. I find that GDP per capita has two statistically significant effects. Controlling for national population size and the count of shocks that a nation experiences, richer nations are less likely to experience a death when shocks occur, and conditional on a positive number of deaths having taken place, richer nations suffer less death.[9] In table 6, the coefficient on the time trend indicates that I cannot reject the hypothesis that there is no time trend with respect to death counts.

In results available on request, I have interacted the time trend with a dummy variable indicating whether the nation has high GDP-per capita, and I find that, controlling for a nation's population, GDP per capita, and count of disasters, richer nations have a negative and statistically significant death-count time trend and poorer nations have a positive time trend.

[9] I cannot reject the hypothesis that the coefficient of GDP per capita's did not change between the 1980s and 1990s.

TABLE 7.—PREDICTED ANNUAL DEATH FROM NATURAL DISASTERS

GDP per Capita	Expected Deaths	Probability that *Death* = 0
$2,000	944	0.287
$8,000	413	0.290
$14,000	180	0.297

The table's predictions are based on the results in table 6, specification (1).
In this table, the population is set at 100 million and the year is set at 1990. The predictions are based on the actual count of natural disasters that a nation experiences.

To provide a sense of the size of these income coefficients, in table 7 I predict death from natural disaster for a poor, a middle-income, and a rich nation. Holding the population at 100 million and the year at 1990, and using the actual shock patterns for each nation, I use the results from column (1) and predict the probability that a nation experiences no deaths from natural disaster; I also predict the count of deaths. The average nation with a GDP per capita of $2,000 experiences 944 deaths from natural disaster per year. If this nation's GNP per capita grew to $14,000, its death toll would fall to 180 per year.[10] In a nation of 100 million, this saving of 764 lives certainly is small as a percentage of total population, but the percentage reduction in overall deaths due to economic development is large. In addition, recent value-of-life research has documented that over time the value of life increases faster than growth in per capita GNP (Costa & Kahn, 2004; Hammitt, Liu, & Liu, 1998).[11]

The results in table 6 aggregate death counts caused by earthquakes, extreme temperature events, floods, landslides, and windstorms. To test whether a nation's income per capita has different effects on death counts by disaster category, in table 8 I report separate ZINB estimates of equation (3) by disaster category. GDP per capita has a negative and a statistically significant effect on reducing deaths from all five subcategories. One way to judge the income coefficient's magnitude is to compare it with the coefficient on the total count of category disasters. Based on this metric, floods and windstorms have the largest income effect. Relative to other shocks such as earthquakes, in order to hold the death count constant, a nation would need a smaller increase in its GDP per capita to offset the shock.

The distribution of national income as well as its mean plays a role in determining deaths from natural disaster. Holding population and GDP per capita constant, a higher Gini coefficient indicates that more people are living in poverty. The poor face greater exposure than the rich to natural-disaster risk. Richer people can afford to live in safer communities and are more likely to be educated and better able to process and to react to information warning them about an upcoming shock such as a hurricane (Bresnahan, Dickie, & Gerking, 1997). The poor are more likely to live in disaster-prone areas and to live and work in structures that are unlikely to withstand the shock.[12] The poor living in informal settlements may not be able to benefit from government regulatory and zoning codes. All else equal, deaths from earthquakes are higher in nations with higher income inequality (see table 5). Based on the ZINB estimates reported in table 6, the income Gini coefficient has a positive effect on death counts. Based on the results in column (2) of table 6, a nation would have the same death count from natural disasters if its income Gini coefficient were 1 standard deviation higher or its GDP per capita were $6,500 lower. This is a very large effect.

HYPOTHESIS 2: Geography is a key determinant of death from disaster.

The results in table 4 establish that a nation's geography is a key determinant of its probability of experiencing a natural disaster. There are large cross-continental differences in the propensity to experience a disaster shock and the deaths caused by these disasters. Table 4, column (1), shows that the Americas, Asia, and Europe are exposed to more shocks than Africa. The Asia dummy in this regression indicates that all else equal, a nation in Asia is 28.5 percentage points more likely to experience a disaster in a given year than one in Africa. Larger nations, those that are more elevated, and those that are farther from the equator are more likely to experience shocks.

Controlling for the count of disasters, geography matters in determining death counts. Table 6, column (2), shows that relative to Africa, nations in Asia and the Americas have the highest death counts. The Europe dummy in this specification is statistically insignificant. This ZINB regression model's results indicate that a nation's elevation has a negative effect on death counts, whereas distance from the equator raises death counts. The ZINB models reported in table 8 disaggregate death counts by disaster type. As shown there, elevation has a negative and statistically significant effect in reducing deaths from windstorms, whereas distance from the equator raises deaths from earthquakes.

HYPOTHESIS 3: Institutional quality insulates against death.

To test the hypothesis that nations with better institutions suffer less death from natural disasters, I focus on several empirical proxy measures for institutional quality. These

[10] The average number annual of deaths per capita from natural disasters is an example of a cross-national environmental statistic that should decline monotonically as national per capita income increases. This prediction distinguishes natural disasters from other environmental indicators such as ambient sulfur dioxide or carbon dioxide emissions. The environmental-Kuznets-curve literature has sought to test for a nonmonotonic relationship between environmental quality and national per capita income. Recent studies such as Schmalensee, Stoker, and Judson (1998) and Harbaugh, Levinson, and Wilson (2002) have tested whether specific environmental indicators at first grow worse with economic development and then improve as national per capita income increases further.

[11] Both Costa and Kahn (2004) and Hammitt et al. (2000) estimate cross-sectional hedonic wage regressions to recover the implicit price of job death risk at several different points in time. In each year, the OLS coefficient on job fatality is scaled up to calculate a value of life.

[12] Klinenberg (2002) documents that in the 1995 heat wave in Chicago, the elderly and blacks were over-represented among the 485 people killed.

TABLE 8.—DETERMINANTS OF ANNUAL NATIONAL DEATH BY DISASTER CATEGORY

	Zero-Inflated Negative-Binomial Regressions				
	(1) Earthquakes	(2) Extreme temperature	(3) Floods	(4) Landslides	(5) Windstorms
Total count of category disasters	0.8015	0.6594	0.1711	0.5670	0.1959
	(0.2480)	(0.1311)	(0.1051)	(0.0802)	(0.0642)
Log population	0.3394	0.5034	0.5598	−0.0114	0.4205
	(0.6245)	(0.1898)	(0.1358)	(0.0539)	(0.1928)
GDP per capita	−0.1597	−0.0701	−0.1061	−0.0606	−0.1763
	(0.0659)	(0.0333)	(0.0271)	(0.0134)	(0.0370)
Time trend	−0.0278	0.0174	0.0183	−0.0226	0.0323
	(0.0381)	(0.0207)	(0.0203)	(0.0118)	(0.0222)
America dummy	2.4369	1.7035	0.6852	0.8213	2.1161
	(1.1335)	(0.6819)	(0.5674)	(0.3424)	(0.5419)
Asia dummy	2.1137	0.9969	0.0065	0.9308	1.5357
	(0.9867)	(0.4887)	(0.3850)	(0.3620)	(0.6084)
Europe dummy	0.5208	0.0945	−0.4367	0.9021	0.3053
	(0.8698)	(0.8955)	(0.5347)	(0.3514)	(0.4692)
Elevation	−1.1119	−0.6257	0.0730	0.0201	−1.6361
	(1.2623)	(0.4994)	(0.2638)	(0.1554)	(0.4046)
Absolute value of latitude	0.0880	0.0358	−0.0153	0.0006	0.0055
	(0.0337)	(0.0273)	(0.0214)	(0.0086)	(0.0270)
Population density	0.1802	−0.3030	0.0883	−0.1595	−0.1171
	(0.4314)	(0.1542)	(0.0787)	(0.0601)	(0.0639)
Percent of land area within 100 km of ice-free coast	−0.0589	2.7589	−0.8470	0.0619	−0.0080
	(1.7250)	(1.1222)	(0.4865)	(0.2762)	(0.7114)
Constant	−1.1120	−3.7181	−0.6907	3.4391	0.6637
	(8.0691)	(2.4203)	(1.1910)	(0.6698)	(1.9515)
	Zero-Inflated Logit Model				
Total count of disasters	−44.4116	−24.7587	−22.4835	−25.9561	−31.5880
	(1.7851)	(0.5399)	(0.1772)		
Constant	24.4203	22.9155	20.8345	23.3212	27.6260
	(0.1642)	(0.3423)			
Ln α	1.8102	0.3760	0.8301	−0.3881	1.1236
	(0.0137)	(0.1231)	(0.0719)	(0.1412)	(0.0558)
α	6.1119	1.4565	2.2936	0.6783	3.0759
	(0.0837)	(0.1793)	(0.1650)	(0.0958)	(0.1717)
Observations	1,415	1,415	1,415	1,415	1,415
Nonzero observations	205	121	582	188	402
P-value for the continent dummies	0.052	0.089	0.464	0.041	0
P-value for geography variables	0.06	0.084	0.297	0.047	0
log likelihood function	−1,263.29	−742.12	−3,530.66	−1,015.303	−2,451.792

Each column of this table reports a separate estimate of a zero-inflated negative binomial (ZINB) model. As presented in equation (3) in the text, the ZINB model has two equations. The lower panel of the table reports the logit model estimates the probability that nobody in a given nation in a given year died from a natural disaster. The upper panel reports the results from the negative-binomial regression. Standard errors are presented in parentheses. The standard errors are adjusted for within-nation clustering. The omitted category is African nations.

include a nation's democracy level, income inequality, ethnic fragmentation, and World Bank indicators of good governance.

Democracies may be better suited to achieve political accountability. Such governments may take proactive steps to adapt to such shocks and to mitigate their impact when they do occur. In a democracy, the free media flourish, and this contributes to greater political accountability and may reduce corruption. In such a setting, politicians who want to be reelected and know that their constituents are informed about their activities have a greater incentive to take actions that protect their constituents (Besley & Burgess, 2002).

To test the hypothesis that there is less death from disaster in democracies, in the ZINB estimates of equation (3) reported in table 6, column (3), I add the polity measure to the specification. All else equal, democracies do experience less death from disaster. The coefficient estimate is borderline statistically significant. The coefficient estimate indicates that an extra standard-deviation increase in the democracy index and an extra $2,200 of income have equal effect on the death count.[13] In column (4) in table 6, I drop national income per capita. In this case, the democracy coefficient more than doubles in size.

A second set of indicators of national institutional quality is within-nation income and ethnic heterogeneity. If social capital is harder to build in more heterogeneous societies, then institutional quality and heterogeneity measures could be negatively correlated. In more heterogeneous communities, the probability of public participation in civic life is lower and productive public goods are less likely to be

[13] It is plausible that under-reporting of deaths in nondemocracies leads to an underestimate of the effect of democracy in reducing natural-disaster deaths.

TABLE 9.—OLS VERSUS IV ESTIMATES OF KEY EXPLANATORY VARIABLES

	Coefficient				
	Natural Disasters		Industrial Disasters		
Explanatory Variable	OLS	IV Using Settler Mortality	OLS	IV Using Settler Mortality	Explanatory Variable's Standard Deviation
Real GDP per capita	−0.0811	−0.0523	−0.0255	−0.0234	6.4605
	(0.0146)	(0.0295)	(0.0023)	(0.0036)	
Average protection against expropriation risk	−0.3473	−0.1994	−0.0681	−0.1119	1.499
	(0.0617)	(0.1121)	(0.0101)	(0.0176)	
Democracy	−0.0104	−0.0746	−0.0017	−0.0508	6.6063
	(0.0141)	(0.0435)	(0.0027)	(0.0097)	
Regulatory quality	−0.6905	−0.6463	−0.1805	−0.3175	0.6564
	(0.1556)	(0.3669)	(0.0222)	(0.0491)	
Voice and accountability	−0.2942	−0.4561	−0.1228	−0.2246	0.7997
	(0.1160)	(0.2669)	(0.0186)	(0.0351)	
Rule of law	−0.7169	−0.4108	−0.1676	−0.1887	0.8511
	(0.1228)	(0.2312)	(0.0165)	(0.0292)	
Control of corruption	−0.3493	−0.4938	−0.1484	−0.1899	0.8855
	(0.1170)	(0.2838)	(0.0154)	(0.0296)	

Dependent variable = log(1 + total deaths from disaster).

The unit of analysis is a nation-year. Each entry in the table reports a separate estimate of b from equation (4) in the text. Controlling for the log of a nation's population, continent fixed effects, a time trend, and a nation's absolute value of latitude and elevation, the table reports the coefficient on the explanatory variable. Robust standard errors are reported in parentheses. In addition to the controls, there is only one explanatory variable in each regression. The regressions are estimated for a subset of 36 nations reported in table 1 that Acemoglu et al. (2001) report data on settler mortality risk for.

supplied (Alesina et al., 1999; Alesina & Ferrara, 2000; Costa & Kahn, 2003). Based on World Value Survey micro data, Knack & Keefer (1997) conclude that trust and civic norms are stronger in nations with higher and more equal incomes, and in those that are less polarized along lines of class or ethnicity. In more ethnically fragmented nations, middle-class support for redistribution is lower (Alesina, Glaeser, & Sacerdote, 2001; Luttmer, 2001). One form of redistribution that could reduce the death count from natural disasters is an active government enforcing building codes and zoning laws.

To test the heterogeneity hypothesis, I include the income Gini measure and the ethnic fragmentation measure in columns (3) and (4) of tables 5 and 6. A consistent finding across all of the regression estimates is that nations with higher income inequality have higher death rates from natural disasters. This result reflects the combination of two separate factors. First, a high Gini coefficient, holding GDP per capita constant, indicates a larger share of a nation's population is poor. Second, social capital and trust in government institutions are harder to build in more unequal societies.

Unlike the income Gini estimates, the ethnic fragmentation results tell a more complicated story. In the earthquake results in table 5, ethnic fragmentation is always statistically insignificant. It has a negative coefficient in columns (1) and (5) and a positive coefficient in columns (3) and (4). Based on the ZINB estimate reported in table 6, columns (3) and (4), nations with higher ethnic fragmentation have lower death counts.[14] This result is not driven by any outlier nations or by a particular continent.

Comparative studies have investigated the determinants of economic performance as a function of institutional quality in the present while instrumenting for the latter using historical national variables (Acemoglu et al., 2001, 2002). I follow this approach to study the robustness of OLS estimates. I use the nation year total death count from disasters and estimate regressions of the form

$$\log(1 + Death_{jt}) = controls_{jt} + b \times (Institutional\ Quality_{jt}) + U_{jt}. \tag{4}$$

Controlling for a nation's population and geography, I seek to compare OLS and IV estimates of b in equation (4). In table 9, the explanatory variable will be either a nation's GDP per capita, its average protection against expropriation risk, its democracy index, or governance quality measures from the World Bank. Due to the high correlation of these variables, I only include one institutional quality measure at a time.

In table 9, I report various estimates of b from equation (4) using Acemoglu et al.'s (2001) historical settler mortality rate as an instrument for institutional quality today.[15] They argue that settler mortality in the past affected the types of settlements created in these colonies and this in turn determined such nations' early institutional quality. If institutional quality persists over time, then settler mortality represents an exogenous measure of institutional quality. Of the 73 nations reported in table 1, I am able to assemble IV data for 36. Based on the settler mortality instrument of Acemoglu et al. (2001), the OLS and IV estimates are quite

[14] Alesina et al. (2003) study how these fragmentation measures correlate with economic indicators. They find that ethnic diversity is negatively correlated with schooling attainment and number of telephones per worker. In my data set the correlation between ethnic fragmentation and GDP per capita is −0.45. Alesina et al. (1999) used U.S. city- and county-level data to document that the production of productive public goods such as education, roads, and sewers was lower in more fragmented areas.

[15] To make this table's output manageable, I only report the estimate of b in equation (4) from each regression and suppress all other regression output.

comparable. In results available on request, I have also estimated IV regressions of equation (4) using the settler mortality variable and a nation's population density in 1500 (see Acemoglu et al., 2002). The IV estimates change very little when I use both instruments.

Deaths from industrial disasters, such as the 1984 accident at the Union Carbide pesticide manufacturing plant in Bhopal, India, offer another test of the role of income and good institutions in protecting the populace from death risk. An extreme pollution-havens hypothesis would predict that poorer nations actively recruit risky industrial plants by promising not to enforce environmental or safety regulations. If this were the case, then EM-DAT data would show that high-poverty nations have higher industrial accident death counts. Rich countries would avoid such deaths by adopting regulations that pushed mobile dangerous plants abroad, and then, when industrial disasters did occur, just as with natural disasters, the rich countries would have the resources to mitigate the disaster's death consequences. If this were the case, regression estimates of equation (4) for deaths from industrial disasters would reveal a steeper negative income and institutions elasticity than similar estimates for random natural disasters. The results in presented in the right two columns of table 9 reject this hypothesis. Using a nation's deaths from industrial disasters as the dependent variable, I find a smaller institutions effect on deaths from industrial disasters than in the natural-disaster regressions reported in the left columns of table 9.

V. Conclusion

Natural disasters can affect several different aspects of an economy, ranging from long-run growth rates to natural-resource prices (Skidmore & Toya, 2002; Prestemon & Holmes, 2002). Such disasters as earthquakes, floods, windstorms, extreme temperature events, and landslides can also impose significant death counts. Between 1990 and 2002, 4,300 natural disasters took place, killing 815,077 people.[16] This paper has used cross-national data for 73 nations to test hypotheses concerning the role of income, geography, and institutions in mitigating death counts from natural disasters.

I reject the hypothesis that richer nations experience fewer shocks or are lucky enough to experience weaker disaster shocks than those experienced by poorer nations. In the face of an equal quantity and quality of shocks to those in poorer nations, richer nations suffer less death from natural disasters. As shown in table 7, if a nation with a population of 100 million experienced a GDP per capita increase from $2,000 to $14,000, that nation would suffer 764 fewer natural-disaster deaths a year.

Geography and institutions also play a role in shielding a nation from death. Relative to other continents, African nations experience fewer natural disasters and, all else equal, suffer less death from natural disasters. Unlike other measures of economic performance, natural-disaster deaths are lower for nations closer to the equator.

Institutions play a role in shielding the population from natural-disaster death. Less democratic nations and nations with more income inequality suffer more death. Both OLS and instrumental variables estimates indicate that nations with stronger institutions suffer lower national death counts from disasters. Why this is the case requires future research. One possible mechanism is corruption. Government corruption could raise death counts through the lack of enforcement of building codes, infrastructure quality, and zoning.

[16] These facts are based on the entire EM-DAT database covering 210 nations.

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