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Gerald R. Ford School of Public Policy
The University of Michigan
Ann Arbor, Michigan 48109-1220

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Coping With Disaster: The Impact of Hurricanes on International Financial Flows, 1970-2001

Dean Yang
University of Michigan

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Dean Yang*

Gerald R. Ford School of Public Policy
and Department of Economics,
University of Michigan

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Abstract

How well do countries cope with the aftermath of natural disasters? In particular, how well do international financial flows buffer economic losses from disasters? This paper focuses on hurricanes (one of the most common and destructive types of disasters), and examines the impact of hurricane damages on resource flows to affected countries. Due to the potential endogeneity of disaster damage, I exploit instrumental variables constructed from meteorological data on hurricanes. Instrumental variables estimates indicate that disaster damages lead to increases in national-level net inflows of migrants' remittances, foreign lending, and foreign direct investment. These types of flows respond rapidly, within the first year after damages. Official development assistance (ODA) also responds positively to hurricane damage, but with a lag of roughly two years. On average, total inflows from these sources within the following four years amount to roughly four-fifths of estimated damages. The null hypothesis of full insurance of hurricane disaster damages cannot be rejected. By contrast, ordinary least squares estimates find essentially no response of international flows to disaster damages, highlighting the importance of an instrumental variables approach in this context.

Keywords: risk-sharing, insurance, official development assistance, foreign aid, remittances, foreign direct investment, international lending, natural disasters, hurricanes
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* Email: deanyang@umich.edu. Address: 440 Lorch Hall, 611 Tappan Street, University of Michigan, Ann Arbor, MI 48109. I have valued feedback and suggestions from Kathryn Dominguez and Jim Hines. HwaJung Choi and Eric Hendrickson provided superb research assistance.

1 Introduction

Natural disasters cause tremendous losses of human life, as well as substantial economic damages. From 1970 to 2001, natural disasters killed an estimated 2.69 million people, injured another 2.65 million, and led to US$955 billion in economic damages worldwide (see Table 1).[1] Individual disasters, too, can have appalling tolls; the 1970 hurricane in Bangladesh killed some 300,000 people. It is not uncommon for estimated economic losses from disasters to amount to substantial fractions of countries' economic output. For example, damages from the 1973 drought in Burkina Faso amounted to 104% of gross domestic product, while those from Hurricane Mitch in Honduras in 1998 came to 38% of GDP. More generally, 39% of world population lives in countries that had experienced disaster damages of 3% of GDP or more in some year between 1970 and 2001.

Given the destructive power of many natural events, and their largely unpredictable nature, it is important to understand how countries cope with the aftermath of disasters. This paper examines how international financial flows buffer the economic losses from natural disasters. In particular, I focus on damage caused by hurricanes, one of the most common and destructive types of disasters.[2] Wind storms, the disaster type that includes hurricanes, caused an estimated 611,000 deaths, 517,000 injuries, and US$278 billion in damages worldwide from 1970 to 2001. 71% of world population lives in 'hurricane-exposed' countries: those hit by hurricanes or that were within 100 miles of a hurricane center at some point during that time period.[3] Of course, geographically large countries such as China, India, or the U.S. may have hurricane-exposed areas but have substantial fractions of their populations far from such areas. If one limits the country sample to geographically smaller countries, those with less than 250,000 square kilometers in land area,[4] then 51% of population is located in hurricane-exposed countries.

A key contribution of this paper is to take a worldwide view in examining systematically the impact of disaster damage on international financial flows. I examine four types of flows—official development assistance (ODA), foreign loans, migrants' remittances, and foreign direct investment—and estimate the responses of such flows to disaster damages, on average across many countries. Surprisingly little research exists on this topic. Existing work uses small, selected

[1] All figures in this paragraph are compiled from estimates in EM-DAT: the OFDA/CRED International Disaster Database. Damage figures are in 1995 US dollars. Population figures are for 2001, from World Development Indicators 2004.

[2] While 'hurricanes' typically refer to events in the Atlantic and eastern Pacific, I use the term in this paper to encompass similar events that are known elsewhere as 'typhoons' and 'tropical cyclones'.

[3] Author's calculation using meteorological data on hurricanes to be described in Section 2.2. Population data are for 2001, from World Development Indicators 2004.

[4] With this size cutoff, the largest countries remaining are the U.K. (240,880 sq. km.) and Guinea (245,720 sq. km.).

samples, and so is not likely to be globally representative. Benson and Clay (2004), in a case study of three countries, find that disasters had little impact on total foreign aid flows. Albala-Bertrand (1993) studies 28 individual natural disaster occurrences, and finds that capital flows and unrequited transfers typically increase after the events; however, the sample is a selection of 28 severe disasters, and may not be representative of more 'typical' disasters.

A central concern in estimating the impact of disaster damage is that reported disaster damages provided by national governments or international organizations may be influenced by the desire to attract financial inflows. For example, damage estimates may be exaggerated when international inflows are expected to be small, leading estimates of the impact of damage on financial flows to be understated. In addition, unobserved third factors may influence both international flows and the size of damages suffered (if disasters occur), also potentially leading to biased estimates.

An innovation of this paper is its approach to dealing with the potential endogeneity of disaster damage reports. I use objective meteorological data on hurricane events to construct instrumental variables for disaster damage. The occurrence of hurricanes is highly predictive of disaster damages experienced by countries in particular years, and it is plausible that hurricanes have their effect on financial flows primarily via the damages they cause.

Instrumental variables estimates indicate that disaster damages lead to increases in national-level net inflows of migrants' remittances, foreign lending, and foreign direct investment. These types of flows respond rapidly, within the first year after damages. Official development assistance (ODA) also responds positively to hurricane damage, but with a lag of roughly two years. On average, total inflows from these four sources amount to roughly 80% of estimated damages. The null hypothesis of full insurance of disaster damages by these types of international flows cannot be rejected. By contrast, ordinary least squares estimates find essentially no response of these international flows to disaster damages, highlighting the importance of an instrumental variables approach in this context.

This paper is part of a currently quite thin literature on the economics of disasters. Kahn (2005) examines heterogeneity in the impact of natural disasters on disaster deaths, focusing on the role of institutions in moderating death tolls. Hines and Jaramillo (2004) examine the impact of natural disasters on economic growth.[5]

[5] While not explicitly about disasters *per se*, Miguel, Satyanath, and Shanker (2004) is also related in that it uses rainfall shocks to instrument for economic growth in estimating the impact of growth on civil conflict. Paxson (1992) examines the impact of rainfall shocks on household savings in rural Thailand.

Two highly related bodies of research are those on risk-sharing arrangements at the international level, on the one hand, and among individual households in rural communities, on the other. On the international level, research tends to conclude that there is relatively little smoothing of national-level consumption variability via international risk-sharing arrangements (for example, Tesar (1993, 1995)). On the other hand, there is substantial microeconomic evidence of risk-sharing (although not complete insurance) among households in developing countries (for example, Townsend (1995), Udry (1994), and Ligon, Thomas, and Worall (2002)). This paper provides evidence that certain types of international flows appear to share risk across countries in the aftermath of disaster events.

Finally, this paper's findings on the response of migrants' remittances to disaster damage relate to research on migration as a risk-coping mechanism for households in poor countries. Rosenzweig and Stark (1989) document the risk-reducing aspects of the spatial distribution of daughters after marriage in rural India. At the international level, it is commonly posited that remittance flows from overseas buffer economic shocks in the migrants' home countries (for example, Ratha 2003), but this claim has been empirically untested until now.

The remainder of this paper is organized as follows. Section 2 provides background on hurricanes worldwide, and discusses the data on hurricanes. Section 3 considers the theoretical role of international financial flows flows in sharing risk (in particular, disaster risk) across countries. Section 4 discusses relevant econometric issues, presents the empirical evidence, and conducts several robustness checks. Section 5 discusses the magnitude of the empirical results. Section 6 concludes.

2 Hurricanes: overview and data sources

2.1 What are hurricanes?

Hurricanes are severe storms that originate over tropical oceans.[6] The term 'hurricane' is typically used to describe severe tropical storms in the Atlantic and east Pacific, but the same type of event is known as a 'typhoon' in the western Pacific and simply a 'tropical cyclone' in the Indian Ocean and Oceania. A tropical storm is classed as a hurricane if sustains winds in excess of 74 miles (119 kilometers) per hour.

Hurricanes only originate over warm tropical waters with a surface temperature of at least

[6]Much of the background description of hurricanes presented here is based on Smith (1992), Alexander (1993), and Bryant (1991).

79 degrees F (26 degrees C). Therefore, due to cooler sea surface temperatures, hurricanes never form in the South Atlantic Ocean or the eastern South Pacific Ocean. In addition, formation of hurricanes requires a zone of low barometric pressure in combination with rotating winds (a 'vortex'), ruling out hurricane formation and persistence within 5 degrees of the equator: the earth's Coriolis force is too weak near the equator to generate sufficient rotating winds.

Figure 1 helps illustrate the typical architecture of a hurricane (it is an aerial view of Hurricane Mitch approaching Honduras on October 26, 1998.) The center of a hurricane (the 'eye') is a circular area of low pressure and calm air typically 20-30 miles (roughly 30-50 km.) in diameter. Surrounding the eye are spiral arms of storm clouds. The spiral-shaped area of weather disturbance can be anywhere from 60-900 miles (roughly 100-1,500 km.) in diameter, but the area of hurricane-force winds is typically smaller. Formation of hurricanes can take place over several days, or as quickly as within 12 hours. Hurricanes will typically last 2-3 days, with the broader storm (including periods with less than hurricane-force winds) lasting for 4-5 days in total.

Hurricanes wreak damage of three general types. First, hurricanes are accompanied by a *storm surge*, a rise in the sea level due to wind-driven waves and low atmospheric pressure. Storm surges can range from 4 feet (1.2 meters) for the smallest hurricanes to 18 feet (5.5 meters) or more for the strongest ones. They are usually the most deadly aspect of hurricanes, and also cause extensive property damage alongside destruction of crops and salt contamination of agricultural land. The storm surge caused by the 1970 Bangladesh hurricane was reported to have reached 30 feet (9 meters). Second, *strong winds* can cause substantial structural damage as well as defoliation of crops. The third type of damage is due to *flooding* due to heavy rainfall, which can also cause landslides in sloped areas. While the storm surge and winds are strongest near the eye of the hurricane, the effects of flooding can be felt hundreds of miles away and can last well beyond the dissipation of hurricane-force winds.

2.2 Hurricane data

Objective data on hurricanes worldwide are available from two U.S. government agencies: the NOAA Tropical Prediction Center (for Atlantic and eastern North Pacific hurricanes) and the Naval Pacific Meteorology and Oceanography Center/Joint Typhoon Warning Center (for hurricanes in the Indian Ocean, western North Pacific, and Oceania). Via detailed post-event analysis, these agencies create what are known as 'best tracks' of individual hurricanes: positions (latitude and longitude) of hurricane centers at 6-hourly intervals, combined with intensity information (wind speed and barometric pressure). These best tracks incorporate information from a variety of sources, such as reconnaisance aircraft, ships, and satellites. While best tracks may be reported as far back as 1851, the data quality is likely to be highest since the early 1960s and the widespread use of meteorological satellites (Chu et al 2002).[7]

Figure 2 shows an example of smoothed hurricane best tracks, with data for the western North Pacific area in 1985. Figure 3 displays all 6-hour segments of hurricane best tracks that are associated with hurricane-force winds, from 1949 to 2001. Hurricanes clearly manifest themselves most predominantly in tropical oceans, and tend to eventually lose force upon striking a continental land mass (although some hurricanes may extend far inland). While hurricanes originate in the tropics, they can often extend into temperate areas, as evidenced by the profusion of hurricanes all along the U.S. Atlantic coast and the temperate coast of East Asia and Japan.

The best track data naturally take hurricanes as the unit of analysis, and so in their raw form give no indication of the countries which may have been affected. However, the empirical analysis to follow will take place at country level, and on an annual basis (the unit of observation is a country-year). So I construct two types of hurricane event variables at the country-year level. The first is a count of hurricane 'landfalls' in a given country and year. I define a landfall as occurring when the center of a hurricane crosses the border of a country. Second, I make use of counts of hurricane 'near-landfalls', which I define as a hurricane center passing within 100 miles (160 kilometers) of a country's borders. The use of near-landfalls acknowledges that hurricanes can have large effects on countries via heavy rains and flooding that can extend much further than the storm surge and strong winds near the eye.[8]

Table 2 displays the number of hurricane landfalls and near-landfalls for each country that experienced at least one of either event between 1970 and 2001.[9] There are a total of 570 landfalls and 564 near-landfalls during the time period. Countries in the table are sorted according to region, country size category, landfalls, and near-landfalls. (The country size category is included because the empirical analysis to follow will examine heterogeneity in the impact of hurricanes along this dimension.) The country with the largest number of landfalls is the Philippines, with

[7]Detailed descriptions of these data files are provided in Jarvinen et al (1984), Davis et al (1984), and Chu et al (2002). The data files from these two sources have been placed in a consistent format by Unisys Weather and are publicly accessible at <http://weather.unisys.com/hurricane/index.html>.

[8]Identification of landfalls and near-landfalls requires the hurricane best tracks to be overlaid with a world map that includes political boundaries of countries. This was accomplished using ArcGIS software. The best tracks used are simply line segments connecting 6-hourly hurricane centers. A line segment was considered a 'hurricane segment' if hurricane-force winds were achieved at either of the two endpoints of the line segment.

[9]My use of the term 'country' encompasses territorial bodies such Puerto Rico, Guam, and Mayotte that are not independent states, as data are often collected separately for such entities.

90, followed by China (86), Japan (62), Mexico (47), the United States (40), Australia (39), Vietnam (34), and Madagascar (16). Among 'small' countries, the countries with the largest numbers of landfalls are Vanuatu (9), New Caledonia (7), the Bahamas (5), Guam (5), Fiji (5), and the Dominican Republic (4). Asterisks indicate that a country will not be included in the empirical analyses to follow because it lacks the necessary data on other variables. 71 countries are listed in Table 2, of which 58 have sufficient data to be included in the empirical analysis for at least one outcome.

3 The impact of disaster damage in theory

When a country experiences a major disaster, how should we expect international financial inflows to change? A basic theoretical result is that if there is a Pareto-efficient allocation of risk across individual entities (in this case, individual countries) in a risk-sharing arrangement, individual consumption should not be affected by idiosyncratic income shocks.

Consider N countries, indexed by i. Countries have an uncertain income in each period t, $y^i_{s_t}$, depending on the state of nature $s_t \in S$. A representative household in country i consumes $c^i_{s_t}$, and experiences within-period utility of $U_i\left(c^i_{s_t}\right)$ at time t. Let utility be separable over time, and let instantaneous utility be twice differentiable with $U_i' > 0$ and $U_i'' < 0$. For the allocation of risk across countries to be Pareto-efficient, the ratio of marginal utilities between countries in any state of nature must be equal to a constant:

$$\frac{U_i'\left(c^i_{s_t}\right)}{U_j'\left(c^j_{s_t}\right)} = \frac{\omega_j}{\omega_i}, \text{ for all } i,\, j,\, s_t, \text{ and } t,$$

where ω_i and ω_j are the Pareto weights of countries i and j. Countries' marginal utilities are proportional to each other, and so consumption levels between countries move in tandem.

Let utility be given by the following constant absolute risk aversion function:

$$U_i\left(c^i_{s_t}\right) = \frac{-e^{-\theta c^i_{s_t}}}{\theta}.$$

Then, following (among others) Mace (1991), Cochrane (1991), Altonji, Hayashi, and Kotlikoff (1992) and Townsend (1994), we can obtain a relationship between individual country i's consumption and average consumption across countries $\overline{c}_{s_t}$:

$$c^i_{s_t} = \overline{c}_{s_t} + \frac{\ln \omega_i - \frac{1}{N}\sum_{j=1}^{N} \ln \omega_j}{\theta} \tag{1}$$

Efficient risk-sharing implies that individual countries' consumption levels depend here only on mean world consumption $\overline{c}_{s_t}$ and an effect determined by the country's Pareto weight relative to other countries'. Because this latter term is constant over time, then *changes* in consumption for particular countries will depend only on the change in mean world consumption. Said another way, countries face only aggregate *global* risk.

The key question is whether idiosyncratic risk or aggregate risk dominates in practice, as this will determine the extent to which consumption can be smoothed. The empirical analysis to follow will examine the impact of disaster damage from hurricanes, which are by their nature only local (not global) phenomena. So in principle one might expect substantial ability of countries to smooth consumption in the face of hurricane-related disaster risk.

How might this cross-country risk-sharing be carried out in practice? First, countries might simply make unrequited transfers or gifts to other countries experiencing negative shocks. Microeconomic studies among households of the insurance role of gifts and remittances include Lucas and Stark (1985), Ravallion and Dearden (1988), Rosenzweig and Stark (1989), Platteau (1991), and Cox, Eser, and Jimenez (1998). Second, countries could make loans to one another. Among others, Eaton and Gersovitz (1981), Kletzer (1984) and Grossman and Van Huyck (1988) have underlined the function of sovereign debt as a smoothing device.[10] And third, transfers of assets across countries can be a way of sharing risk.[11]

Adapting Fafchamps and Lund (2003), let consumption of country i in state s_t be the sum of income $y^i_{s_t}$, net inflows of unrequited transfers $r^i_{s_t}$, net borrowing $b^i_{s_t}$, and the change in assets $\Delta a^i_{s_t}$:

$$c^i_{s_t} = y^i_{s_t} + r^i_{s_t} + b^i_{s_t} + \Delta a^i_{s_t}$$

So then we can rewrite equation (1) as:

$$r^i_{s_t} + b^i_{s_t} + \Delta a^i_{s_t} = -y^i_{s_t} + \overline{c}_{s_t} + \frac{\ln \omega_i - \frac{1}{N}\sum_{j=1}^{N} \ln \omega_j}{\theta} \tag{2}$$

[10] And at the microeconomic level, see (for example) Townsend (1995), Udry (1994), and Rosenzweig (1988) for evidence on credit as a consumption-smoothing mechanism.

[11] For microeconomic studies in this vein, see for example Rosenzweig and Wolpin (1993), Lim and Townsend (1998), and Fafchamps, Udry, and Czukas (1998).

This equation can be transformed into an empirically testable specification as follows. First, separate income $y^i_{s_t}$ into:

$$y^i_{s_t} = \widetilde{y}^i - z^i_{s_t},$$

where $\widetilde{y}^i$ is the permanent component of income and $z^i_{s_t}$ is the transitory component of income. Only the transitory component depends on the state of the world. Note that I define $z^i_{s_t}$ so that larger amounts are *bad* for income, to correspond with the shock measure I will be using in the empirics (damage from disasters).

The function of Pareto weights and the permanent income component $\widetilde{y}^i$ can be captured by a country fixed effect γ_i. The mean world consumption level $\overline{c}_{s_t}$ can be represented subsumed within a time effect ϕ_t. Also allow a random component ε_{it}, a mean-zero error term. Then equation (2) becomes:

$$r^i_{s_t} + b^i_{s_t} + \Delta a^i_{s_t} = z^i_{s_t} + \gamma_i + \phi_t + \varepsilon_{it} \tag{3}$$

The empirical test of this paper will be based on equation (3), where the outcome variables are net transfers, net borrowing, and asset changes separately, as well as the sum of all these flows. Specifically, the net transfer measures will be net official development assistance, and net remittances from overseas migrants. Net borrowing will be loans minus repayments from international lenders. And asset changes will be represented by net foreign direct investment and net portfolio investment.

This paper will focus on a particular type of transitory shock $z^i_{s_t}$, damages from disasters, using instrumental variables constructed from hurricane events. It is of interest to examine which of the potential types of international financial flows—transfers, loans, or asset sales—appear to respond positively to disaster damages (and thus act as insurance).

Two additional null hypotheses will be useful to test, when the outcome variable in equation (3) is taken to be all types of international flows combined. First, is the coefficient on inflows with respect to damages $z^i_{s_t}$ greater than zero? If yes, then this will be evidence that at least some insurance is taking place. Second, can we reject the null of full insurance, i.e., that the coefficient on $z^i_{s_t}$ is equal to one?

4 Empirical evidence

This section documents the impact of disaster damage (instrumented by hurricane landfalls and near-landfalls) on international financial flows. I first describe other data sources used in the empirical analysis, and then describe summary statistics. I then present the empirical results from the first stage analysis (predicting disaster damage using hurricane instruments) and the second stage IV analysis (impact of disaster damage on international financial flows). The remainder of the empirical section conducts several robustness checks.

4.1 Other data sources

Aside from the data on hurricane events described above, another crucial type of data required is on disaster damages experienced by countries over time. I use disaster damage data from EM-DAT: the CRED/OFDA International Disaster Database, maintained by the Center for Research on the Epidemiology of Disasters (CRED), Université Catholique de Louvain.[12] Estimated disaster damages are reported at the country-year level, in currency units. These estimates include both direct costs (such as damage to property, infrastructure, and crops) and the indirect losses due to reductions in economic activity. Disaster damage estimates are meant to correspond only to the year of the associated event, and not ongoing effects that persist beyond the disaster year. In subsidiary analyses, I also use data on number of people killed from EM-DAT.

The sources of disaster impact data in EM-DAT are varied, and include national governments, UN agencies, non-governmental organizations, insurance companies, research institutes and the media. Active data collection for EM-DAT started in the late 1960s, and retrospective research was necessary to record disasters prior to that date, stretching back to 1900 (Guha-Sapir, Hargitt, and Hoyois 2004). The analysis to follow will make use of data in EM-DAT from 1966 to 2001.[13]

The outcome variables of interest in the empirical analysis will be various categories of net international financial flows. The following come from the World Bank's World Development Indicators 2004 (WDI 2004). *Official development assistance* is net disbursements of loans and grants made on concessional terms to promote economic development in developing countries. These figures include official aid to transition economies of Eastern Europe and the former Soviet Union. *Net financial flows* are disbursements of loans and credits minus repayments of principal. I calculate the sum of WDI 2004's separately-reported net financial flows from the International Bank for Reconstruction and Development (IBRD), the International Development Association (IDA), the IMF, regional development banks (such as the Inter-American Development Bank, the Asian Development Bank and the African Development Bank), and private and other lenders.

[12] These data are available at <www.em-dat.net>.

[13] The empirical analysis takes 1970 as the starting year, but examines lagged effects of disaster damages up to 4 years before.

Foreign direct investment is net inflows in the reporting country less net outflows by the reporting country of investment to acquire a lasting management interest (10 percent or more of voting stock) in an enterprise operating in an economy other than that of the investor. *Portfolio investment* encompasses transactions in equity and debt securities, and excludes liabilities constituting foreign authorities' reserves (LCFAR). Data on net flows of *migrants' remittances* are from IMF Balance of Payments Statistics 2004, and are the sum of separately-reported items for workers' remittances, compensation of employees, and migrants' transfers.[14]

The following adjustments are made to these data. All figures reported in currency amounts are converted to 1995 US dollars using GDP deflators in WDI 2004 and the 1995 local currency/US dollar exchange rate. To facilitate analysis of data across economies of vastly different sizes, the data on disaster damages and international financial flows will be expressed as fractions of GDP. Because disasters may also affect the denominator of these statistics (the level of GDP), I use GDP in prior years as the denominator. In particular, because I will be interested in the effects of disaster damages up to 4 years before, I use mean GDP from 5, 6, and 7 years prior to a given observation as the denominator for all damage and international flow variables. An analogous adjustment is made for the number of people killed due to disasters, where the denominator is mean population in the 5-7 years prior.

Finally, I drop countries from the analysis for a given outcome variable if data for that outcome is available for less than three years between 1970 and 2001 for that country. This change does not affect the empirical results, as the outcomes for countries that have only one or two observations of non-missing data are entirely explained by the country fixed effect and the country-specific linear time trend. To maximize relevance for the samples for the main outcome variables, in summary statistics tables I drop observations that lack sufficient data for inclusion in any of the international flow outcome regressions.

The resulting samples contain between 3,121 and 4,016 observations (depending on the outcome variable), and between 127 and 170 countries. The countries that actually experience hurricane landfalls or near-landfalls are listed in Table 2. The remaining countries serve as controls, and primarily contribute to the estimates by improving the estimates of global year fixed effects. The panel is unbalanced, with the number of observations varying across countries depending on

[14] It is standard in studies of remittances to group these three categories together (see Ratha 2003). Workers' remittances refer to transfers from persons abroad for a year or longer. Compensation of employees refers to transfers from persons overseas for less than a year. Migrants' transfers are transfers of financial assets by migrants when moving from one country to another.

data availability.[15]

4.2 Summary statistics

Table 3 presents summary statistics for the observations included in the analyses. The top third of the table presents summary statistics for all observations. Summary statistics for disaster damage and hurricane events are for all observations included in at least one international flow regression. Disaster damage as a percentage of GDP has a mean of 0.72%, and the mean in levels is US$234 million. On average across country-year observations, two out of 100,000 inhabitants were killed due to disasters. The means of hurricane landfalls and near-landfalls are 0.118 and 0.097, respectively. ODA as a share of GDP has a mean of 8.78%, but in some countries this figure is quite high: the 90th percentile of this variable is 22.55%. Other variables appear more evenly distributed worldwide. The mean of remittances as a share of GDP is 2.82%, with a 90th percentile of 7.81%. Mean net financial flows as a share of GDP is 2.61%, and the corresponding figures for FDI and portfolio investment are 2.13% and -0.03%, respectively.

The remaining thirds of Table 3 present corresponding summary statistics, but separately for observations with a hurricane landfall or near-landfall (middle third of table) and for observations without any such hurricane events (bottom third). It is clear that countries experiencing some hurricane event report greater damages as a share of GDP (the mean is 2.11%) than those without a hurricane event (where the mean is 0.55%), as well as larger fractions of population killed.

However, the basic means do not provide a consistent indication of whether international flows are larger for the hurricane-affected observations. For example, mean ODA as a share of GDP is higher in observations without a hurricane event, while mean FDI as a share of GDP is higher among hurricane-affected observations. Of course, such comparisons have no necessary causal interpretation: it could simply be that hurricane-prone countries have higher or lower international flows for reasons independent of hurricanes (such as their general development status).

4.3 First-stage estimates: impact of hurricanes on disaster damage

In examining the impact of disaster damage on international financial flows, disaster damage reports compiled in the EM-DAT database cannot plausibly be taken, in and of themselves, as exogenous with respect to the outcomes in question. For example, reverse causation is likely to

[15] The regression results are robust to conducting the analysis on a more balanced panel (limiting the sample to countries that are observed for 10 or more years), as will be discussed in subsection 4.5.

be a problem. If large financial inflows are occurring in response to disasters, countries or international agencies have no need to exaggerate damage figures. But when flows are not forthcoming, disaster damages may be exaggerated to attract more resources. This would lead the estimated effect of damage on financial inflows to be negatively biased. There may also be omitted variable problems, as when worsening economic conditions or a breakdown of government functions leads to declines in financial inflows and an increase in vulnerability to disasters (perhaps due to deteriorating disaster warning systems, deteriorating infrastructure, declines in property maintenance, etc.).

To deal with problems of reverse causation or omitted variables, this paper uses an instrumental variables approach. I instrument for disaster damage with events that are plausibly exogenous with respect to the international flows of interest: hurricane landfalls and near-landfalls.

As the first-stage outcome to be instrumented will be disaster damage as a share of GDP, the impact of a hurricane is likely to be heterogeneous according to a country's physical size: a hurricane striking a country as large as China (with an area of 9,327,450 sq. km.) is likely to have a much smaller impact as a share of GDP than a similar event striking a small country like Belize (22,800 sq. km.). So I will use as instruments the number of hurricane landfalls and near-landfalls, as well as these variables interacted with indicators for different country size groups, defined roughly by quartiles of the worldwide distribution of land areas: small-medium countries, with between 60,000 and 250,000 sq. km. in land area; medium-large countries, between 250,000 and 770,000 sq. km.; and large countries, with land area greater than 770,000 sq. km. The omitted category will be small countries, with less than 60,000 sq. km. in land area.[16]

For disaster damage as a share of GDP in country i and year t, DAM_{it}, the first-stage regression equation will be as follows:

$$\begin{aligned} DAM_{it} = {} & \alpha_0 + \alpha_1 H_{it}^L + \alpha_2 \left(H_{it}^L * SIZEQ2_i\right) + \alpha_3 \left(H_{it}^L * SIZEQ3_i\right) + \alpha_4 \left(H_{it}^L * SIZEQ4_i\right) \\ & + \alpha_5 H_{it}^N + \alpha_6 \left(H_{it}^N * SIZEQ2_i\right) + \alpha_7 \left(H_{it}^N * SIZEQ3_i\right) + \alpha_8 \left(H_{it}^N * SIZEQ4_i\right) \\ & + \gamma_i + \phi_t + \delta_i \left(D_i * TREND\right) + \varepsilon_{it} \end{aligned} \tag{4}$$

H_{it}^L is the number of hurricane landfalls in country i and year t, while H_{it}^N is the corresponding number of near-landfalls. $SIZEQ2_i$, $SIZEQ3_i$, and $SIZEQ4_i$ are dummy variables for the second through fourth country land area quartiles (small-medium, medium-large, and large, re-

[16] Land area for each country is taken to be the mean from 1968-1972 (or, if unavailable, mean over earliest subsequent 5-year period).

spectively). Country fixed effects γ_i control for time-invariant differences across countries. Year fixed effects ϕ_t control for changes common to all countries in the same year. $TREND$ is a linear time trend. Country-specific time trends (δ_i, the coefficient on a country indicator D_i interacted with the time trend) help account for the effect of slow-moving changes over time that occur throughout the sample period, and that differ across countries. ε_{jt} is a mean-zero error term.

Serial correlation in the outcome variables is likely to be a problem in this panel dataset, biasing OLS standard error estimates downward (Bertrand, Duflo and Mullainathan (2004)), so standard errors allow for an arbitrary variance-covariance structure within countries (standard errors are clustered by country).

The coefficient α_1 on H^L_{it} is the impact of a hurricane landfall on deviations from country-specific trends in disaster damage as a share of GDP for 'small' countries, and the coefficients α_2 through α_4 represent the difference in the impact of a hurricane landfall for countries in the corresponding larger size category (with respect to the impact for 'small' countries). The coefficients α_5 through α_8 on the near-landfall variable H^N_{it} and interaction terms are interpreted analogously.

Table 4 presents results for estimation of equation (4). The sample is limited to observations with complete data on official development assistance as a fraction of GDP. Column 1 of the table presents results without the inclusion of the country size interaction terms. Both hurricane landfalls and hurricane near-landfalls lead to increases in disaster damage as a share of GDP. The estimates are individually statistically significant (landfalls at the 5% level and near-landfalls at the 10% level), and jointly statistically significant at the 5% level (according to an F-test reported at the bottom of the table). Each hurricane landfall leads to increases in disaster damage in the same year of roughly one-half percent of GDP. While the point estimate on hurricane near-landfalls is more than three times the size as the point estimate for landfalls (0.0174), standard errors are too large to reject the hypothesis that the two coefficients are equal in size.

Column 2 of the table presents regression results where the country size interaction terms are included. The hurricane landfalls main effect (representing the impact for countries in the smallest size group) has become four times larger in magnitude compared to the previous regression, and is statistically significant at the 10% level. Coefficients on the hurricane landfall interaction terms are negative and of increasing magnitude as land area increases, indicating that the impact of landfalls on damage relative to GDP declines with land area. Coefficients on the two largest country size interaction terms are each statistically significantly different from zero. The patterns exhibited by the hurricane near-landfalls variables are qualitatively very similar, although none of those coefficients are individually statistically significantly different from zero.

As a group, the hurricane landfall and near-landfall variables and associated interaction terms are strong instruments. The F(8,147)-statistic of the test of joint significance of the eight instruments is 2.24, with a p-value of 0.028.

The second-stage instrumental variables results will examine the impact of instrumented disaster damage not only in the current year, but also for up to four years before. So the actual first stage regression equation will be analogous to equation (4) above, but including also lagged hurricane landfall and near-landfall variables and interaction terms for 1 to 4 years before.

Table 5 presents results for estimation of this expanded version of equation (4) where the outcome variable is current-year disaster damage as a share of GDP. The coefficients in the first column are for the instruments in the current year, and so are analogous to those in column 2 of Table 4. The results for these coefficients are very similar to those in column 2 of Table 4, and the current-year instruments jointly achieve similar levels of statistical significance (the F-test of joint significance has a p-value of 0.0154). As might be expected, instruments in other years are not jointly statistically significant (according to reported F-tests), and are rarely individually statistically significant.[17] The F-test of the joint statistical significance of all 40 hurricane variables and interaction terms has a p-value of 0.0000, suggesting that weak instrument issues are not a problem in this setting.[18]

Table 5 is the first stage for disaster damage in the current year. Disaster damage 1 through 4 years before are estimated using analogous regressions but for damage as a share of GDP in the corresponding prior years. Results are not shown due to space considerations, but they offer no surprises: instruments for given years are only jointly statistically significant when they correspond to the year of disaster damage (i.e., instruments for 2 years before are only significant when the outcome is disaster damage 2 years before), and F-tests for the joint significance of all instruments routinely reject the null hypothesis at high significance levels.

[17] One seemingly anomalous result is the coefficient on the number of hurricane landfalls in year -3 for small-medium countries, which is positive and statistically significant at the 10% level. This coefficient turns out to be entirely driven by two countries which experienced very large disaster damage three years after a hurricane landfall (Honduras in 1974 with 52% damage, and Laos in 1993 with 23%). The main results to follow are not driven by these countries: repeating the analysis when excluding Honduras and Laos removes the anomalous first-stage coefficient but yields second-stage results very similar to those to be presented later.

[18] As noted above, the first-stage regression results in Tables 4 and 5 are for the sample of observations included in the second-stage regressions for ODA as the outcome variable. First-stage regressions for the samples corresponding to the other outcome variables do not differ in substantial ways.

4.4 Instrumental variables estimates: impact of disaster damage on international financial flows

The first stage regressions with hurricane landfalls, near-landfalls, and country-size interaction terms as instruments (as in Table 5) allow construction of predicted damage as a share of GDP for country i in year t, $\widehat{DAM}_{it}$, as well as predicted damages 1 to 4 years before: $\widehat{DAM}_{it-1}$, $\widehat{DAM}_{it-2}$, $\widehat{DAM}_{it-3}$, and $\widehat{DAM}_{it-4}$. These predicted damages are the independent variables of interest in a regression specification based on equation (3) above. The instrumental variables regression equation for international financial flows Y_{it} for country i in year t is:

$$\begin{aligned} Y_{it} &= \beta_0 + \beta_1 \widehat{DAM}_{it} + \beta_2 \widehat{DAM}_{it-1} + \beta_3 \widehat{DAM}_{it-2} + \beta_4 \widehat{DAM}_{it-3} + \beta_5 \widehat{DAM}_{it-4} \\ &\quad + \gamma_i + \phi_t + \delta_i \left(D_i * TREND \right) + \varepsilon_{it} \end{aligned} \tag{5}$$

As in the first stage equation, the second-stage equation also includes country fixed effects, year fixed effects, and country-specific linear time trends. The country-specific linear time trends are useful to separate the effect of disaster damages from the influence of long-running time trends in outcome variables in particular countries.[19]

The coefficients of interest are β_1 through β_5 on current and lagged predicted damage as share of GDP.[20] Because both dependent and independent variables are expressed as fractions of GDP (from 5-7 years before), these coefficients should be interpreted as 'replacement rates'. (For example, a coefficient of 0.1 would be a replacement rate of 10%.)

Table 6 presents both ordinary least squares and instrumental variables estimates of the impact of disaster damage on five types of international financial flows (each in a separate regression). Panel A of the table presents OLS results, and Panel B the IV results.

While the coefficients on disaster damage in the OLS results are mostly positive in sign, they are all very small in magnitude (in no case are they larger than 0.021 in absolute value) and mostly not statistically significantly different from zero (except for damages 1 to 4 years before in the FDI regression and for damages 4 years before in the remittance regression).

The IV estimates, on the other hand, tell a very different story. For four out of the five types

[19] While these would not be necessary if hurricane events themselves showed no apparent time trends, it turns out that hurricane landfalls and near-landfalls do appear to have become more common in aggregate over the course of the 32-year period of analysis. An OLS regression (with 32 observations) of the number of hurricane landfalls in each year from 1970 to 2001 on a constant and a linear time trend yields a coefficient on the time trend of 0.35 (std. err. 0.12), and an R-squared of 0.2283.

[20] The instrumental variable estimates are actually calculated in a one-step procedure using STATA's ivreg command.

of financial flows (all except portfolio investment), net inflows respond positively to instrumented disaster damages. The coefficients on current and lagged damages in the ODA regression are all positive in sign, with the coefficient for damage 2 years before being largest in magnitude and statistically significantly different from zero. This coefficient indicates a large replacement rate of damages 2 years before by ODA of 0.196.

Coefficients on damages in the current year and 1 year before are also all positive where the outcome variables are net financial flows, remittances, and FDI. Statistical significance at conventional levels is achieved in the net financial flows and remittance regressions for damage in the current year and 1 year before, with coefficients ranging from 0.073 to 0.179. In the FDI regression, only current-year damages are statistically significant at the conventional level, with a coefficient of 0.171. For portfolio investment, on the other hand, the coefficients on damages are all substantially smaller in magnitude, actually negative in sign, and never statistically significantly different from zero.

4.5 Alternative subsamples

It is important to test the robustness of the main empirical results in alternative subsamples. Table 7 presents regression results from a range of additional specifications of the main regression equation (5), for the four types of international flows that appear to respond to disaster damages: ODA, net financial flows, remittances, and FDI.

In the first row of the table, the most statistically significant regression coefficients from Table 6 (the original sample) are presented for each of the four outcome variables: the coefficient on damage 2 years before for ODA, on damage 1 year before for both net financial flows and remittances, and on damage in the current year for FDI. The remaining rows of the table display the corresponding coefficients when the estimates are conducted using alternative subsamples.

The samples used in the regressions of Table 6 are unbalanced: the countries included in the sample vary substantially in the number of observations, ranging from 3 to 32 observations over the 1970-2001 period of analysis. A concern may be that country-specific time trends may not be estimated well when countries have few observations included in the sample. In addition, one might be concerned that patterns of entry into and exit from the sample of countries with few observations may be driving the empirical results. So the second row of Table 7 presents coefficient estimates when the sample is restricted to countries that have data on the given outcome variable for 10 or more years. The results provide no indication that the presence of countries with very few observations in the main regressions affects the fundamental conclusions. All coefficients remain positive and highly statistically significantly different from zero, and are very similar in magnitude to the corresponding coefficients in the original sample.

The first stage results of Tables 4 and 5 indicate that the impact of hurricanes on disaster damage as a share of GDP is largest for countries with the smallest land area. It is thus worth asking whether the main empirical results hold mainly for the subsample of smaller countries. So the next set of results in Table 7 presents coefficient estimates separately for the sample of countries with land area less than 250,000 sq. km. (roughly the sample median), and for countries above this threshold. The coefficient estimates for the subsample of smaller countries appear very similar in magnitude and statistical significance to those in the original sample. This is in stark contrast to results for the larger subsample of countries: indeed, three out of the four coefficient estimates are actually negative (with the exception of that in the FDI regression). That said, the coefficient estimates for the larger-country subsample are very large, so that not a great deal further can be said about how they differ from the original regression results. Nonetheless, it is probably fair to conclude that the original regression results are indeed driven by the smaller countries in the sample.

Finally, it seems worthwhile to examine how the results differ when looking separately at the countries by development status, as reliance on international flows to cope with disasters may vary on this dimension. The final two rows of Table 7 present coefficient estimates for the sample of less-industrialized countries, on the one hand, and for the highly industrialized countries on the other.[21] Net financial flows and ODA are primarily flows from multilateral funding institutions and donor agencies, and are zero for all industrialized countries, so no regression results are reported for these cells. For the remaining two outcomes, the results also appear to be driven by less-industrialized countries. The coefficients for the less-industrialized countries are essentially identical in magnitude and statistical significance to those in the original sample. The coefficients for the highly industrialized countries are similar in magnitude, but they are not statistically significantly different from zero.

[21] The 'highly industrialized countries' are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and United States.

4.6 Size of IV vs. OLS estimates

In Table 6, OLS estimates of the impact of disaster damage are consistently smaller in magnitude than the IV estimates, and are mostly not statistically significantly different from zero. In the discussion of the first-stage equation above, I hypothesized that intentional reporting biases may lead to downward bias in the estimated impact of damage on inflows of resources from overseas: if inflows are expected to be low for whatever reason, damage reports may be intentionally exaggerated to stimulate more inflows. In addition, third factors such as worsening economic conditions or a breakdown of government functions may lead to declines in financial inflows and an increase in disaster damage (if disasters occur), also generating a negative bias.

An alternative explanation for the difference in the OLS and IV estimates is possible, however, that has nothing to do with reverse causation or omitted variables. The IV estimates isolate disaster damages that are due specifically to hurricanes, while the OLS estimates are for damages from all disasters. It may simply be that international flows respond *more* to hurricane damage than to other types of damage, for whatever reason. One can test this hypothesis by repeating the OLS regressions of Table 6 for reported damages specifically from *wind storms*, the disaster type that includes hurricanes (as opposed to damage from all disasters).[22]

Appendix Table 1 presents regression results that are analogous to those in Panel A of Table 6, but where variables for disaster damage as a share of GDP is replaced by disaster damage *from wind storms* as a share of GDP. If the difference between Panel A (OLS estimates) and Panel B (IV estimates) in Table 6 is due simply to the fact that financial flows respond primarily to wind storms and not to other types of disasters, then the results in Appendix Table 1 should be similar to the IV results in Panel B of Table 6. As it turns out, however, there is no evidence in support of this hypothesis: Appendix Table 1's results are instead nearly identical to the OLS results in Panel A of Table 6.

4.7 Other potential sources of bias

A central assumption underlying the instrumental variables estimates of the impact of disaster damage is that hurricanes only affect the outcomes of interest (international financial flows) via their effect on disaster damage. This exclusion restriction would be violated if international financial flows were responding to effects of hurricanes other than recorded economic damages.

[22]The main regression results instrument for damage from *all* disaster types, rather than just wind storm damage, to allow for the possibility that hurricanes may affect damage suffered from other disasters as well. For example, a hurricane may weaken structures and increase property damage from a later earthquake.

The most obvious other potential channels of hurricanes' impacts on inflows are via the number of people killed, and via changes in economic activity (growth). In principle, the damage estimates reported in EM-DAT are meant to include the economic effects of disaster deaths, and more broadly the effects of disasters on economic activity. However, EM-DAT damage reports are explicitly defined as encompassing damages *only in the year of the disaster*, so that lagged effects of disaster deaths, and lagged effects on economic activity overall will not be included in the damage data. It is obvious that deaths have lagged economic effects: those killed are no longer producing output. Disasters may also have lagged effects on economic activity more broadly (that are not captured in the current damage data), to which international flows may be responding. Therefore, the damage estimates (particularly lagged damages) may understate the true economic damages.

In addition, international flows may respond to non-economic motives. For example, foreign aid may respond simply to the number of deaths, independent of any assessment of the economic impact of those deaths.

If some lagged economic effects of disasters are indeed not included in the disaster estimates, and if flows do respond to deaths independent of their economic effects, then the instrumental variables estimates of the impact of disaster damages presented so far will be *overstated*, as inflows that are not directly caused by the observed damages will be attributed to them. One way to test whether this source of bias is important is to simply include as control variables in the IV regressions the number of people killed and changes in real GDP (and lags of these variables).[23] Gauging how inclusion of these controls affects the IV estimates can provide insight into whether these alternative channels are operating, and if so, the direction of bias they generate. If IV estimates decline substantially in magnitude upon inclusion of these controls for alternative channels, this would suggest that the original results are indeed overstated.

Appendix Table 2 presents regression results that are analogous to those in Panel B of Table 6, except that controls are included for number of people killed in disasters (as share of population if years 5-7 before), the change in real GDP (current-year real GDP divided by mean real GDP 5-7 years before), and four lags of these variables.[24] As it turns out, the coefficients on the damage

[23] It is reasonable to believe that number of deaths and overall GDP will be substantially less prone to the type of measurement and misreporting issues that are likely to matter for the economic damage estimates. Deaths are presumably easier to identify and tabulate than economic damages. GDP estimates are generally arrived at using a more systematic methodology than often ad-hoc damage estimates.

[24] The sample sizes of each regression are marginally smaller than those in Panel B of Table 6 because of missing population data for some observations. The regression estimates without control variables for these marginally smaller subsamples are essentially identical to those in Panel B of Table 6.

variables tend to remain similar in size to the previous estimates after inclusion of these control variables, and in some cases they become even larger in magnitude. For example, the coefficient on damage 2 years before in the ODA regression has become roughly a third larger in magnitude. Essentially all the damage variables that statistically significantly predicted international inflows in Table 6 continue to do so here.[25] There appears to be little indication that alternative channels of hurricanes' impacts impart upward bias to the estimated coefficients.

5 Discussion: magnitude of the results

How large are the estimated effects of damages on international inflows? In particular, what is the 'replacement rate' of disaster damages by resource inflows from overseas? Can we reject the null hypothesis of full insurance, that the replacement rate of combined international inflows with respect to disaster damages is 1? In answering these question, it is useful to limit the sample for analysis to countries that have complete data on all four of the main outcome variables, and examine the impact of damages on *total* inflows of funds from these sources combined.

Table 8 presents instrumental variables regression estimates of equation (5), limiting the sample to only those observations that have complete data on ODA, net financial flows, remittances, and FDI. The first four columns of the table have as outcome variables the four types of flows separately, to examine robustness of the original results to this new subsample. In general, the original results still hold, with a few exceptions. There are no longer statistically significant coefficient estimates in the net financial flows regression, although the coefficient on damages 1 year before is of almost the same magnitude as before. In the ODA regression, the coefficient on damages 2 years before remains statistically significant (although now only at the 10% level), while the coefficient on damages 3 years has now become statistically significant at the 10% level. The coefficient on current damages in the remittance regression is now smaller by roughly a third in magnitude, but it remains statistically significant at the 10% level.

The last column of the table presents coefficient estimates for a regression where the outcome variable is the *sum* of the outcome variables in the first four columns—total net inflows from ODA, net financial flows, remittances, and FDI. The coefficients on damages from the current year to 3 years after are all positive in sign, and the coefficient on current damages is large (0.427) and statistically significantly different from zero. This replacement rate of total current inflows to

[25] The exceptions are the coefficients on current damages in the net financial flows and remittances regressions, which have become only marginally statistically significant. However, these coefficients are of essentially the same magnitude as before.

current damages may be considered large: almost half of damages are replaced by current inflows from overseas.

The sum of the individual regression coefficients on all the damage variables in a particular regression is the replacement rate of disaster damages by inflows within four years after the disaster (including the disaster year). This sum of coefficients (and its standard error in parentheses) is reported at the bottom of the table for each outcome variable. It worth noting that the 4-year replacement rate via remittances, 0.284, is statistically significant by itself, and the others are all positive in sign. The coefficient sum in the last column is the replacement rate of total international inflows from the four sources with respect to disaster damages. At 0.844, this is a large coefficient, indicating a replacement rate of more than four-fifths within 4 years of disaster damage. Crucially, the null hypothesis that this coefficient is equal to unity (full insurance) cannot be rejected: the t-statistic on this test is 0.38, with a p-value of 0.707.

6 Conclusion

Disasters exact a huge toll worldwide, both in terms of human casualties as well as economic losses. Until now, however, there has been no systematic assessment of the extent to which international resource flows help buffer countries from disaster losses. This paper fills this gap, focusing on hurricanes—one of the most common and destructive types of disasters.

Disaster damage reports are potentially endogenous, and in particular may be influenced by the desire to attract resource inflows. To deal with this issue, I make use of instrumental variables constructed from meteorological data on hurricanes. Instrumental variables estimates indicate that disaster damages lead to increases in national-level net inflows of official development assistance, migrants' remittances, foreign lending, and foreign direct investment. I document both contemporaneous and lagged effects of damages on resource inflows. On average, total inflows from these four sources amount to roughly four-fifths of estimated damages within four years after a disaster. The null hypothesis of full insurance of disaster damages by these types of international flows cannot be rejected. By contrast, ordinary least squares estimates find essentially no response of international flows to disaster damages, highlighting the importance of an instrumental variables approach in this context.

Valuable future work on this topic could use an analogous instrumental variables approach to understand the impact of damages from other types of disasters (such as earthquakes), to ascertain the generalizability of these results. In addition, it may be of broad interest to document the impact of disasters of various sorts on overall economic growth. I am currently pursuing research in these directions.

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Table 1: Human losses and damages from natural disasters worldwide 1970-2001

Type of disaster	Killed (000s)	Injured (000s)	Damage (1995 US$, 000s)	% of total damage
Drought	877	0	59,865,474	6.27%
Wind storm	611	517	278,302,633	29.13%
Earthquake	573	1,086	299,814,937	31.38%
Flood	206	945	251,450,119	26.32%
Famine	205	0	71,798	0.01%
Epidemic	147	80	1,450	0.00%
Volcano	26	8	5,514,201	0.58%
Earth slide	24	8	4,289,094	0.45%
Extreme temperature	17	6	27,589,390	2.89%
Wave / Surge	3	1	4,659	0.00%
Wild fire	1	2	28,139,750	2.95%
Insect infestation	0	0	251,002	0.03%
Total	2,690	2,652	955,294,507	100.00%

NOTES -- All figures are in thousands. Data are worldwide totals between 1970-2001 from EM-DAT: the OFDA/CRED International Disaster Database, Université Catholique de Louvain, Brussels, Belgium. (Available at www.em-dat.net). Damage figures in EM-DAT converted to constant 1995 US dollars using GDP deflators and exchange rates from World Bank's World Development Indicators 2004. Disaster types in table sorted by number killed. "Wind storm" category includes phenomena variously referred to as cyclones, hurricanes, storms, tornadoes, tropical storms, typhoons, or winter storms.

Table 2: Total number of hurricanes by country, 1970-2001

Region	Country size category	Country	Hurricane landfalls	Hurricane near-landfalls	
Caribbean	Small	Bahamas, The	5	8	
Caribbean	Small	Dominican Republic	4	5	
Caribbean	Small	Haiti	3	4	
Caribbean	Small	Puerto Rico	2	9	*
Caribbean	Small	Virgin Islands (U.S.)	2	8	*
Caribbean	Small	Antigua and Barbuda	2	7	
Caribbean	Small	Dominica	2	4	
Caribbean	Small	St. Kitts and Nevis	1	8	
Caribbean	Small	Bermuda	1	8	
Caribbean	Small	Jamaica	1	3	
Caribbean	Small	Cayman Islands	0	4	*
Caribbean	Small	Barbados	0	3	
Caribbean	Small	St. Lucia	0	3	
Caribbean	Small	St. Vincent and the Grenadines	0	1	
Caribbean	Small-Medium	Cuba	7	6	*
Central America	Small	Belize	3	4	
Central America	Small	Costa Rica	0	3	
Central America	Small	El Salvador	0	1	
Central America	Small-Medium	Nicaragua	4	3	
Central America	Small-Medium	Guatemala	3	6	
Central America	Small-Medium	Honduras	3	4	
Central America	Large	Mexico	47	30	
East Asia	Small-Medium	Korea, Rep.	7	15	
East Asia	Small-Medium	Korea, Dem. Rep.	1	2	*
East Asia	Medium-Large	Japan	62	42	
East Asia	Large	China	86	57	
Eastern Europe	Large	Russian Federation	0	1	
Europe	Small-Medium	Portugal	0	1	
Europe	Small-Medium	United Kingdom	0	1	
Europe	Medium-Large	France	0	2	
North America	Large	United States	40	13	
North America	Large	Canada	8	6	
Oceania	Small	Vanuatu	9	18	
Oceania	Small	New Caledonia	7	12	
Oceania	Small	Guam	5	24	*
Oceania	Small	Fiji	5	8	
Oceania	Small	Northern Mariana Islands	2	16	*
Oceania	Small	Solomon Islands	2	2	
Oceania	Small	Samoa	1	2	*
Oceania	Small	American Samoa	1	2	*
Oceania	Small	Tonga	0	5	
Oceania	Small	Palau	0	4	*
Oceania	Small	Marshall Islands	0	3	*
Oceania	Small	French Polynesia	0	2	
Oceania	Small	Micronesia, Fed. Sts.	0	2	
Oceania	Medium-Large	Papua New Guinea	0	4	
Oceania	Medium-Large	New Zealand	0	1	
Oceania	Large	Australia	39	23	
South America	Large	Colombia	0	2	
South America	Large	Venezuela, RB	0	2	
South Asia	Small-Medium	Bangladesh	8	2	
South Asia	Small-Medium	Sri Lanka	2	4	
South Asia	Large	India	23	12	
South Asia	Large	Pakistan	1	1	
Southeast Asia	Small	Singapore	0	1	
Southeast Asia	Small-Medium	Lao PDR	8	26	
Southeast Asia	Small-Medium	Cambodia	3	10	*
Southeast Asia	Medium-Large	Philippines	90	36	
Southeast Asia	Medium-Large	Vietnam	34	21	
Southeast Asia	Medium-Large	Myanmar	9	5	
Southeast Asia	Medium-Large	Thailand	2	12	
Southeast Asia	Medium-Large	Malaysia	1	0	
Southeast Asia	Large	Indonesia	0	6	
Southern Africa	Small	Mauritius	1	9	
Southern Africa	Small	Mayotte	0	3	*
Southern Africa	Small	Comoros	0	2	
Southern Africa	Small-Medium	Malawi	0	2	
Southern Africa	Medium-Large	Madagascar	16	3	
Southern Africa	Medium-Large	Zimbabwe	1	0	
Southern Africa	Large	Mozambique	6	4	
Southern Africa	Large	South Africa	0	1	
TOTAL			570	564	

NOTES -- Rows of table sorted by region, size, hurricane landfalls, and hurricane near-landfalls. "Landfalls" are hurricane centers passing across a country's borders. "Near-landfalls" are hurricane centers passing within 100 miles of a country's borders. Hurricane counts are totals between 1970-2001. Counts use hurricane best track databases of the NOAA Tropical Prediction Center and the Naval Pacific Meteorology and Oceanography Center/Joint Typhoon Warning Center, combined with GIS data on country borders. Asterisk (*) indicates country lacks sufficient data for inclusion in regression analyses. Country size categories are quartiles of the worldwide distribution of land areas (in sq. km.): small, <60,000; small-medium, >=60,000 and <250,000; medium-large, >=250,000 and <770,000; large, >770,000. Land area for each country is mean from 1968-1972 (or, if unavailable, mean over earliest subsequent 5-year period).

Table 3: Summary statistics, 1970-2001

All observations

	Mean	Std. Dev.	10th pctile.	Median	90th pctile.	Num. Obs.
Damage (% of GDP)	0.72%	10.31%	0.00%	0.00%	0.28%	4,042
Damage (1995 US$, 000s)	233,969	2,543,088	0	0	131,512	4,042
Killed (% of population)	0.0020%	0.0216%	0.0000%	0.0000%	0.0017%	4,016
Number of hurricane landfalls	0.118	0.540	0	0	0	4,042
Number of hurricane near-landfalls	0.097	0.376	0	0	0	4,042
Official development assistance (% of GDP)	8.78%	12.50%	0.08%	4.12%	22.55%	3,369
Remittances (% of GDP)	2.82%	10.79%	-1.16%	0.56%	7.81%	2,559
Net financial flows (% of GDP)	2.61%	4.16%	-0.76%	1.71%	6.93%	2,841
Foreign direct investment (% of GDP)	2.13%	6.83%	-0.58%	0.78%	6.82%	3,135
Portfolio investment (% of GDP)	-0.03%	4.04%	-1.03%	0.00%	2.15%	3,121

Observations WITH hurricane landfall or near-landfall

	Mean	Std. Dev.	10th pctile.	Median	90th pctile.	Num. Obs.
Damage (% of GDP)	2.11%	8.76%	0.00%	0.05%	3.63%	453
Damage (1995 US$, 000s)	1,327,878	7,072,653	0	40,150	2,354,372	453
Killed (% of population)	0.0032%	0.0222%	0.0000%	0.0003%	0.0031%	446
Number of hurricane landfalls	1.053	1.271	0	1	3	453
Number of hurricane near-landfalls	0.863	0.775	0	1	2	453
Official development assistance (% of GDP)	6.56%	10.67%	0.04%	1.73%	19.31%	355
Remittances (% of GDP)	2.02%	3.47%	-0.17%	0.99%	5.79%	327
Net financial flows (% of GDP)	1.96%	2.94%	-0.71%	1.51%	5.18%	294
Foreign direct investment (% of GDP)	2.64%	5.65%	-0.52%	0.92%	7.47%	362
Portfolio investment (% of GDP)	0.48%	2.25%	-0.66%	0.00%	2.87%	356

Observations WITHOUT hurricane landfall or near-landfall

	Mean	Std. Dev.	10th pctile.	Median	90th pctile.	Num. Obs.
Damage (% of GDP)	0.55%	10.47%	0.00%	0.00%	0.12%	3,589
Damage (1995 US$, 000s)	95,897	901,149	0	0	35,000	3,589
Killed (% of population)	0.0018%	0.0216%	0.0000%	0.0000%	0.0015%	3,570
Number of hurricane landfalls	0.000	0.000	0	0	0	3,589
Number of hurricane near-landfalls	0.000	0.000	0	0	0	3,589
Official development assistance (% of GDP)	9.04%	12.67%	0.08%	4.43%	22.94%	3,014
Remittances (% of GDP)	2.94%	11.47%	-1.49%	0.51%	7.97%	2,232
Net financial flows (% of GDP)	2.69%	4.27%	-0.77%	1.77%	7.10%	2,547
Foreign direct investment (% of GDP)	2.07%	6.97%	-0.64%	0.77%	6.62%	2,773
Portfolio investment (% of GDP)	-0.10%	4.21%	-1.14%	0.00%	2.05%	2,765

NOTES-- The unit of observation is a country-year. For variables expressed as % of GDP, GDP in denominator is average of 5-7 years prior to observation. For number killed as % of population, population in denominator is average of 5-7 years prior to observation. All other currency-denominated variables are in constant 1995 US dollars, including those used for % of GDP figures. Sources: IMF Government Finance Statistics; World Bank's World Development Indicators; EM-DAT International Disaster Database; hurricane best track databases of the NOAA Tropical Prediction Center and the Naval Pacific Meteorology and Oceanography Center/Joint Typhoon Warning Center.

<u>Table 4</u>: Impact of hurricanes on disaster damage, 1970-2001
(Fixed effects OLS estimates)

<u>Sample</u>: Observations with data on official development assistance as fraction of GDP.

<u>Dependent variable</u>: Disaster damage as fraction of GDP

	(1)	(2)
Hurricane landfalls	0.0051	0.022
	(0.0025)**	(0.0119)*
Hurricane landfalls * Small-Medium Land Area		-0.0147
		(0.021)
Hurricane landfalls * Medium-Large Land Area		-0.0207
		(0.0119)*
Hurricane landfalls * Large Land Area		-0.0219
		(0.0119)*
Hurricane near-landfalls	0.0174	0.0397
	(0.0093)*	(0.024)
Hurricane near-landfalls * Small-Medium Land Area		-0.014
		(0.030)
Hurricane near-landfalls * Medium-Large Land Area		-0.039
		(0.025)
Hurricane near-landfalls * Large Land Area		-0.0386
		(0.024)
Country fixed effects	Y	Y
Year fixed effects	Y	Y
Country-specific linear time trends	Y	Y
Num. of obs.	3,369	3,369
R-squared	0.19	0.19
F-statistic: joint significance of all hurricane variables	3.09	2.24
P-value	0.0485	0.028

NOTES -- Unit of observation is a country-year. Standard errors in parentheses, clustered by country. Dependent variable is disaster damage divided by mean GDP 5-7 years before. "Small-Medium Land Area" is between 60,000 and 250,000 sq. km. "Medium-Large Land Area" is between 250,000 and 770,000 sq. km. "Large Land Area" is above 770,000 sq. km. (Omitted land area category is small: below 60,000 sq. km.) See Table 3 for variable definitions and other notes.

Table 5: Impact of hurricanes on disaster damage, 1970-2001
(Fixed effects OLS estimates, first stage of IV regression)

Sample: Observations with data on official development assistance as fraction of GDP.

Dependent variable: Disaster damage as fraction of GDP

Year:	Current	1 year before	2 years before	3 years before	4 years before
Hurricane landfalls	0.0206	-0.0056	0.0057	-0.0111	-0.0100
	(0.0138)	(0.0076)	(0.0090)	(0.0092)	(0.0088)
Hurricane landfalls * Small-Medium Land Area	0.0041	0.1115	0.0167	0.0425	0.0202
	(0.0197)	(0.1058)	(0.0245)	(0.0235)*	(0.0255)
Hurricane landfalls * Medium-Large Land Area	-0.0191	0.0062	-0.0034	0.0114	0.0102
	(0.0137)	(0.0078)	(0.0087)	(0.0097)	(0.0088)
Hurricane landfalls * Large Land Area	-0.0205	0.0081	-0.0043	0.0114	0.0090
	(0.0137)	(0.0085)	(0.0089)	(0.0091)	(0.0089)
Hurricane near-landfalls	0.0397	-0.0092	-0.0049	0.0030	-0.0028
	(0.0223)*	(0.0138)	(0.0080)	(0.0084)	(0.0122)
Hurricane near-landfalls * Small-Medium Land Area	-0.0139	-0.0091	-0.0018	-0.0101	0.0056
	(0.0253)	(0.0163)	(0.0199)	(0.0154)	(0.0228)
Hurricane near-landfalls * Medium-Large Land Area	-0.0392	0.0110	0.0039	-0.0054	0.0024
	(0.0227)*	(0.0143)	(0.0084)	(0.0086)	(0.0129)
Hurricane near-landfalls * Large Land Area	-0.0385	0.0092	0.0028	-0.0041	0.0028
	(0.0223)*	(0.0139)	(0.0087)	(0.0087)	(0.0124)
F-statistic: joint significance of hurr. vars. in this year	2.47	1.03	1.25	0.99	0.34
P-value	0.0154	0.4183	0.2734	0.4434	0.9488
F-statistic: joint significance of all hurricane variables	22.77				
P-value	0.0000				
Num. of obs.	3,369				
R-squared	0.2				

NOTES -- Table presents coefficient estimates from a single OLS regression. Unit of observation is a country-year. Standard errors in parentheses, clustered by country. Dependent variable is disaster damage divided by mean GDP 5-7 years before. Regression includes country and year fixed effects, and country-specific linear time trends. Hurricane variables are for 0 to 4 years before. "Small-Medium Land Area" is between 60,000 and 250,000 sq. km. "Medium-Large Land Area" is between 250,000 and 770,000 sq. km. "Large Land Area" is above 770,000 sq. km. (Omitted land area category is small: below 60,000 sq. km.) See Table 3 for variable definitions and other notes.

<u>Table 6:</u> Impact of disaster damage on international financial flows, 1970-2001

<u>Panel A: Ordinary least squares regressions</u>

	Dependent variables (net flows, as fraction of GDP):				
	Official development assistance	Financial flows	Remittances	Foreign direct investment	Portfolio investment
Damage as fraction of GDP:					
In current year	0.012	0.008	0.001	0.007	-0.003
	(0.008)	(0.008)	(0.002)	(0.006)	(0.003)
1 year before	0.012	0.011	0.003	0.018	-0.002
	(0.010)	(0.010)	(0.004)	(0.008)**	(0.003)
2 years before	0.01	0.01	-0.003	0.021	0.001
	(0.014)	(0.009)	(0.005)	(0.006)***	(0.002)
3 years before	0.009	0.008	0.001	0.02	-0.001
	(0.007)	(0.007)	(0.004)	(0.009)**	(0.002)
4 years before	0.006	0.005	-0.007	0.011	0
	(0.004)	(0.003)	(0.003)***	(0.003)***	(0.002)
Country fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
Country-specific linear time trends	Y	Y	Y	Y	Y
Num. of obs.	3,369	2,841	2,559	3,135	3,121
R-squared	0.85	0.39	0.96	0.75	0.38

<u>Panel B: Instrumental variables regressions</u>

<u>Instrumental variables for disaster damage</u>: hurricane landfalls, hurricane near-landfalls, and interactions with country size categories, 0 to 4 years before (see Table 5 for first stage results).

	Dependent variables (net flows, as fraction of GDP):				
	Official development assistance	Financial flows	Remittances	Foreign direct investment	Portfolio investment
Damage as fraction of GDP:					
In current year	0.065	0.083	0.179	0.171	-0.023
	(0.047)	(0.043)*	(0.103)*	(0.066)**	(0.043)
1 year before	0.093	0.073	0.082	0.102	-0.026
	(0.065)	(0.025)***	(0.032)**	(0.083)	(0.045)
2 years before	0.196	0.056	0.057	-0.064	-0.04
	(0.076)**	(0.044)	(0.054)	(0.053)	(0.048)
3 years before	0.083	0.069	0.04	-0.017	-0.049
	(0.065)	(0.045)	(0.069)	(0.047)	(0.041)
4 years before	0.079	-0.045	-0.009	-0.082	-0.032
	(0.085)	(0.057)	(0.078)	(0.057)	(0.031)
Country fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
Country-specific linear time trends	Y	Y	Y	Y	Y
Num. of obs.	3,369	2,841	2,559	3,135	3,121

* significant at 10%; ** significant at 5%; *** significant at 1%

NOTES -- Unit of observation is a country-year. All regressions include country fixed effects, year fixed effects, and country-specific linear time trends. Each column of table is a separate regression. Standard errors in parentheses, clustered by country. All flows are net (inflows minus outflows). "Financial flows" are disbursements of loans and credits less repayments of principal. For variables expressed as fraction of GDP, GDP in denominator is average of 5-7 years prior to observation. See Table 3 for variable definitions and other notes.

<u>Table 7:</u> Impact of disaster damage on international financial flows, 1970-2001
(IV estimates, alternative subsamples)

<u>Dependent variable:</u> <u>Coefficient on damage from:</u>	ODA 2 years ago	Financial flows 1 year ago	Remittances 1 year ago	FDI Current year
<u>Sample definition:</u>				
Original sample	0.196	0.073	0.082	0.171
(estimates from Table 6)	(0.076)**	(0.025)***	(0.032)**	(0.066)**
Countries with 10 or more	0.185	0.073	0.084	0.181
observations	(0.069)***	(0.025)***	(0.033)**	(0.067)***
<u>By land area:</u>				
Land area *less* than 250,000 sq. km.	0.217	0.072	0.086	0.17
	(0.084)**	(0.027)***	(0.039)**	(0.077)**
Land area *greater* than 250,000 sq. km.	-0.079	-0.1	-0.251	0.112
	(0.742)	(0.540)	(0.398)	(0.399)
<u>By development status:</u>				
Less-industrialized countries	0.196	0.073	0.085	0.181
	(0.076)**	(0.025)***	(0.033)**	(0.067)***
Highly industrialized countries	*n.a.*	*n.a.*	0.067	0.213
			(0.144)	(0.611)

NOTES -- Each cell of table is coefficient (standard error) from a separate IV regression, analogous to those in previous table. Land area is mean from 1968-1972 (or, if unavailable, mean over earliest subsequent 5-year period). "Highly industrialized countries" are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and United States. Net financial flows and ODA are zero for all industrialized countries, so no regression results are reported for these cells.

Table 8: Impact of disaster damage on international financial flows, 1970-2001
(Instrumental variables estimates, sample with complete data on all four main flows)

Instrumental variables for disaster damage: hurricane landfalls, hurricane near-landfalls, and interactions with country size categories, 0 to 4 years before (see Table 5 for first stage results).

	Dependent variables (net flows, as fraction of GDP):				
	Official development assistance	Financial flows	Remittances	Foreign direct investment	All four flows combined
Damage as fraction of GDP:					
In current year	0.087	0.016	0.132	0.193	0.427
	(0.065)	(0.049)	(0.073)*	(0.062)***	(0.182)**
1 year before	0.03	0.057	0.09	0.062	0.239
	(0.060)	(0.048)	(0.039)**	(0.067)	(0.156)
2 years before	0.091	0.019	0.035	-0.063	0.082
	(0.052)*	(0.037)	(0.048)	(0.061)	(0.094)
3 years before	0.058	0.036	0.014	0.04	0.148
	(0.033)*	(0.040)	(0.056)	(0.065)	(0.097)
4 years before	-0.001	-0.039	0.013	-0.026	-0.052
	(0.054)	(0.060)	(0.064)	(0.045)	(0.145)
Country fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
Country-specific linear time trends	Y	Y	Y	Y	Y
Num. of obs.	1,686	1,686	1,686	1,686	1,686
Sum of coefficients on all damage variables	0.265	0.089	0.284	0.206	0.844
	(0.187)	(0.158)	(0.135)**	(0.185)	(0.415)**

* significant at 10%; ** significant at 5%; *** significant at 1%
NOTES -- Unit of observation is a country-year. All regressions include country fixed effects, year fixed effects, and country-specific linear time trends. Each column of table is a separate regression. Standard errors in parentheses, clustered by country. All flows are net (inflows minus outflows). "Financial flows" are disbursements of loans and credits less repayments of principal. Dependent variable in last column is sum of dependent variables in first four columns. For variables expressed as fraction of GDP, GDP in denominator is average of 5-7 years prior to observation. See Table 3 for variable definitions and other notes.

<u>Appendix Table 1:</u> Impact of hurricane damage on international financial flows, 1970-2001
(Ordinary least squares regressions)

	Dependent variables (net flows, as fraction of GDP):				
	Official development assistance	Financial flows	Remittances	Foreign direct investment	Portfolio investment
Wind storm damage as fraction of GDP:					
In current year	0.006	0.005	0.003	0.008	-0.003
	(0.004)	(0.005)	(0.003)	(0.007)	(0.004)
1 year before	-0.002	0.006	0.006	0.018	-0.002
	(0.007)	(0.007)	(0.005)	(0.009)*	(0.003)
2 years before	0	0.005	0	0.024	0
	(0.012)	(0.003)	(0.003)	(0.006)***	(0.002)
3 years before	-0.002	0	0.006	0.024	-0.002
	(0.003)	(0.004)	(0.003)**	(0.008)***	(0.003)
4 years before	0	0.007	-0.005	0.011	0
	(0.004)	(0.004)*	(0.002)**	(0.004)***	(0.001)
Country fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
Country-specific linear time trends	Y	Y	Y	Y	Y
Num. of obs.	3,369	2,841	2,559	3,135	3,121
R-squared	0.85	0.38	0.96	0.75	0.38

* significant at 10%; ** significant at 5%; *** significant at 1%
NOTES -- Unit of observation is a country-year. All regressions include country fixed effects, year fixed effects, and country-specific linear time trends. Each column of table is a separate regression. Standard errors in parentheses, clustered by country. All flows are net (inflows minus outflows). "Financial flows" are disbursements of loans and credits less repayments of principal. For variables expressed as fraction of GDP, GDP in denominator is average of 5-7 years prior to observation. See Table 3 for variable definitions and other notes.

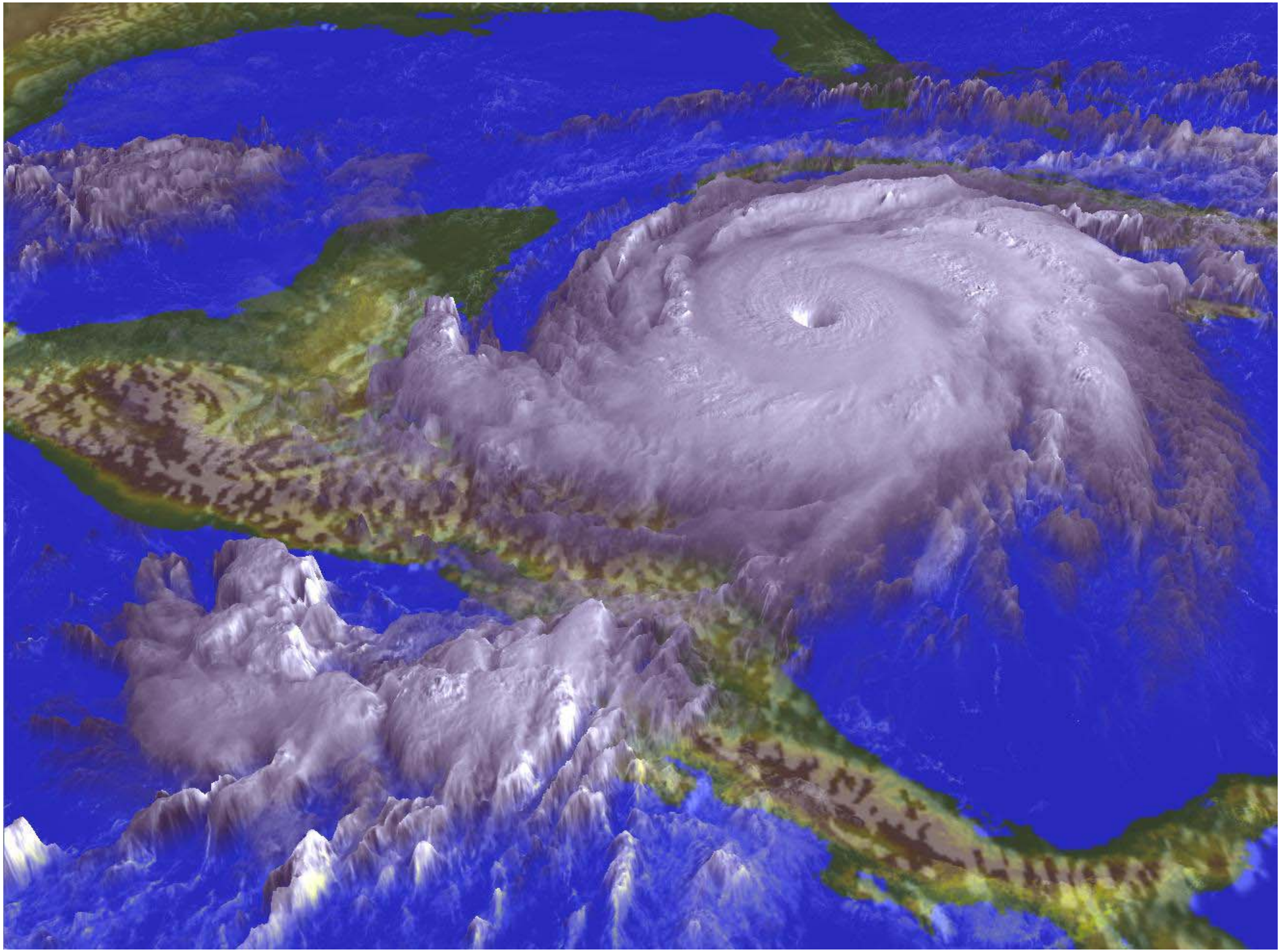
<u>Appendix Table 2:</u> Impact of disaster damage on international financial flows, 1970-2001
(Instrumental variables estimates, controlling for persons killed and economic growth)

<u>Instrumental variables for disaster damage</u>: hurricane landfalls, hurricane near-landfalls, and interactions with country size categories, 0 to 4 years before (see Table 5 for first stage results).

	Dependent variables (net flows, as fraction of GDP):			
	Official development assistance	Financial flows	Remittances	Foreign direct investment
Damage as fraction of GDP (instrumented):				
In current year	0.081	0.104	0.184	0.157
	(0.063)	(0.067)	(0.115)	(0.066)**
1 year before	0.127	0.085	0.08	0.072
	(0.091)	(0.036)**	(0.039)**	(0.096)
2 years before	0.27	0.07	0.053	-0.102
	(0.106)**	(0.053)	(0.066)	(0.067)
3 years before	0.123	0.072	0.036	-0.045
	(0.087)	(0.052)	(0.075)	(0.062)
4 years before	0.125	-0.037	-0.012	-0.126
	(0.100)	(0.061)	(0.087)	(0.071)*
Killed as fraction of population:				
In current year	-3.862	-8.252	-8.016	-7.902
	(7.701)	(8.332)	(12.020)	(10.052)
1 year before	-2.014	-4.534	-0.815	-2.643
	(11.146)	(4.028)	(3.365)	(6.559)
2 years before	-30.066	-4.993	-2.011	8.829
	(18.842)	(4.547)	(3.776)	(5.271)*
3 years before	-10.31	-4.411	-0.681	5.516
	(10.271)	(4.301)	(4.100)	(4.332)
4 years before	-11.127	2.211	1.515	6.605
	(9.404)	(4.406)	(4.088)	(4.224)
Change in real GDP vs. 5-7 years before:				
In current year	0.059	0.043	0.057	0.072
	(0.037)	(0.025)*	(0.032)*	(0.036)**
1 year before	-0.005	0.015	-0.023	0.003
	(0.033)	(0.015)	(0.046)	(0.033)
2 years before	-0.042	-0.04	-0.043	-0.057
	(0.023)*	(0.018)**	(0.045)	(0.029)**
3 years before	0.035	0.006	0.062	0.023
	(0.038)	(0.021)	(0.064)	(0.033)
4 years before	0.011	-0.011	-0.019	-0.018
	(0.030)	(0.021)	(0.049)	(0.023)
Country fixed effects	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y
Country-specific linear time trends	Y	Y	Y	Y
Num. of obs.	3,343	2,841	2,559	3,135

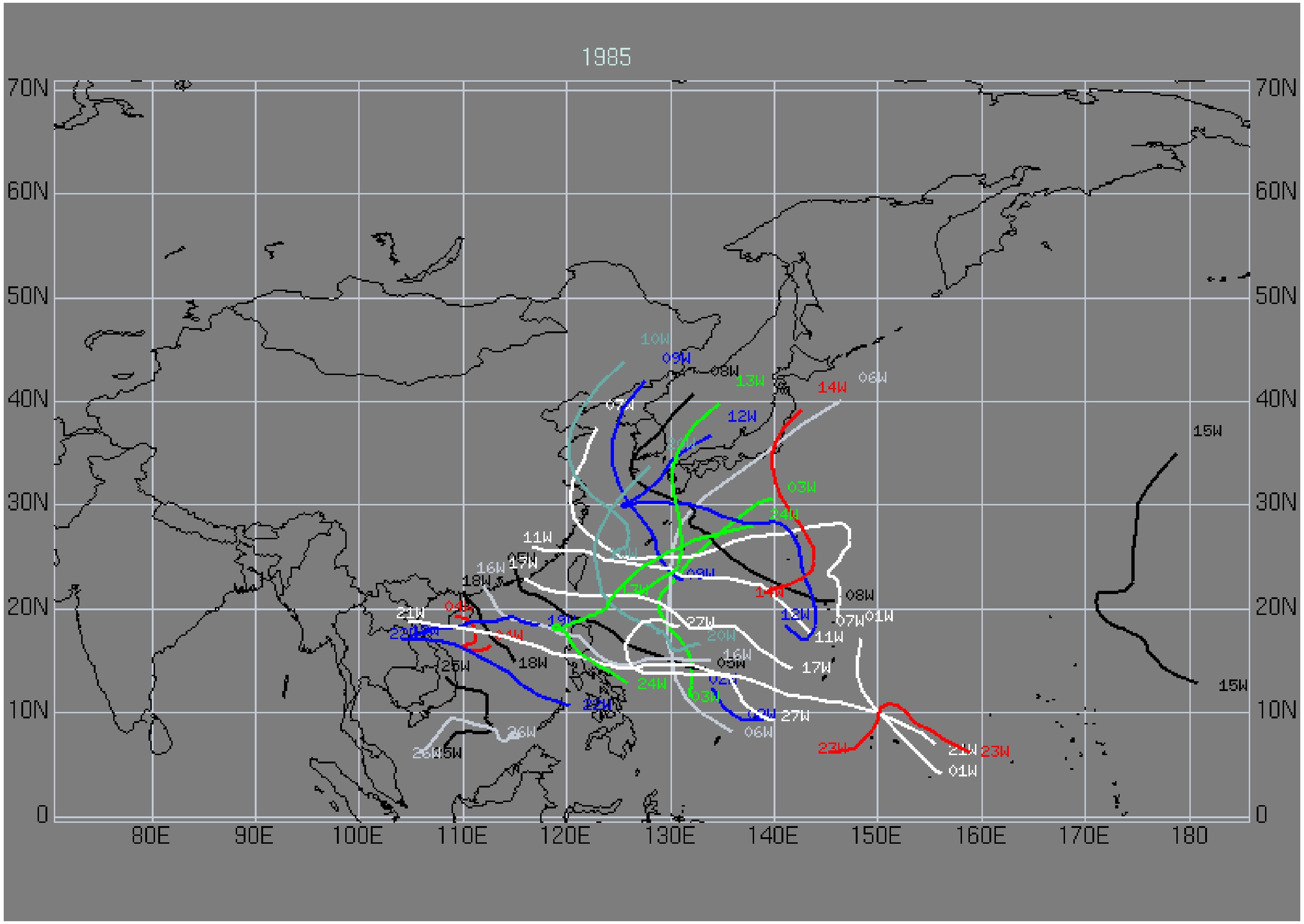
* significant at 10%; ** significant at 5%; *** significant at 1%
NOTES -- Unit of observation is a country-year. All regressions include country fixed effects, year fixed effects, and country-specific linear time trends. Each column of table is a separate regression. Standard errors in parentheses, clustered by country. All flows are net (inflows minus outflows). "Financial flows" are disbursements of loans and credits less repayments of principal. For variables expressed as fraction of GDP, GDP in denominator is average of 5-7 years prior to observation. "Change in real GDP vs. 5-7 years before" is real GDP in given year divided by mean of real GDP 5-7 years before given observation. See Table 3 for variable definitions and other notes.

Figure 1 **Hurricane Mitch approaching Honduras, October 26, 1998**



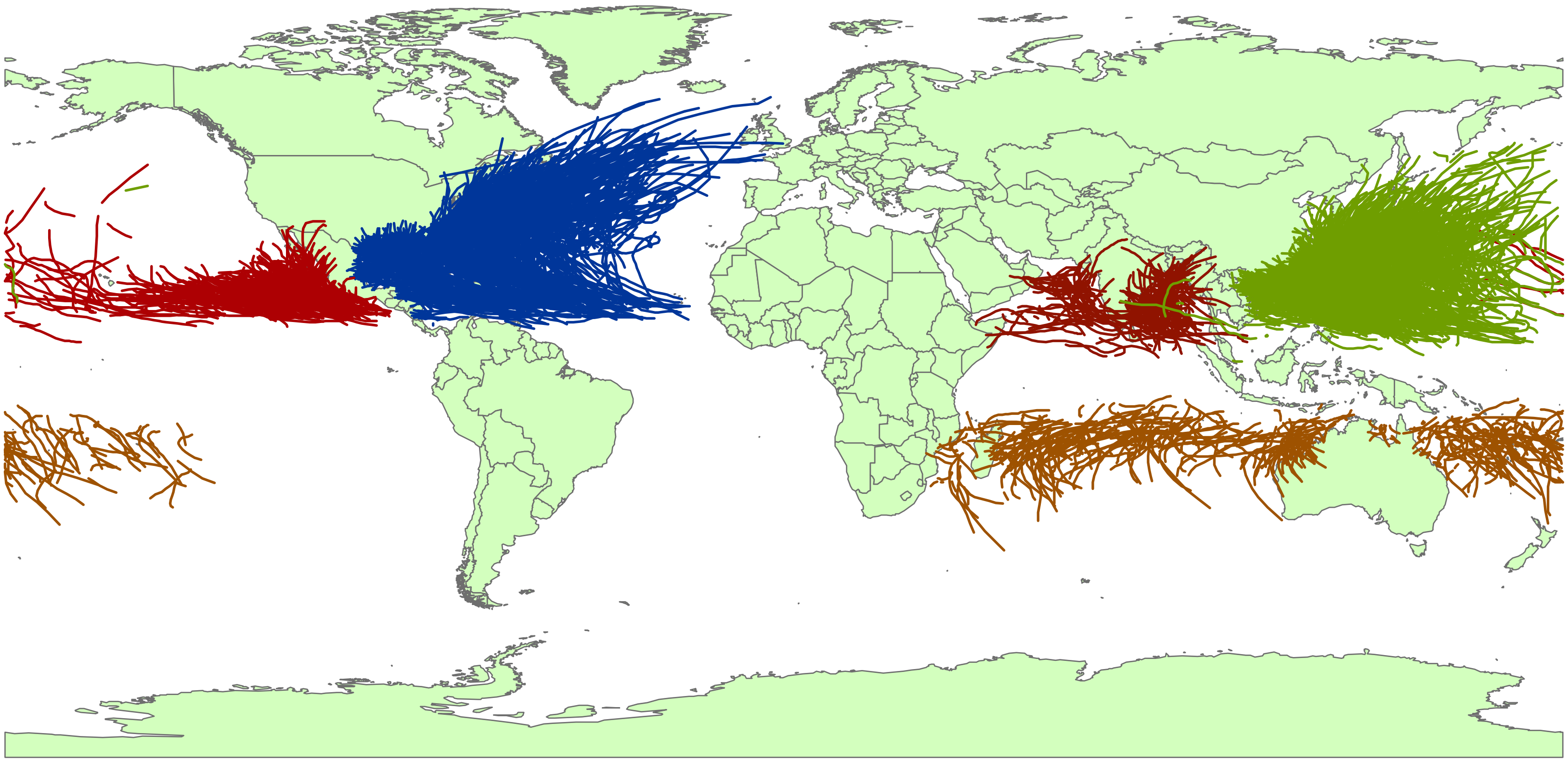
Source: http://rsd.gsfc.nasa.gov/rsd/images/Mitch.html.

<u>Figure 2</u> Western North Pacific best tracks, 1985



<u>Source</u>: Naval Pacific Meteorology and Oceanography Center/Joint Typhoon Warning Center. Link provided in Chu et al (2002) and available at <http://www.npmoc.navy.mil/jtwc/best_tracks/TC_bt_report.html>.

<u>Figure 3</u> Hurricane best tracks worldwide, 1949-2001



<u>Sources</u>: Hurricane best track databases of the NOAA Tropical Prediction Center and the Naval Pacific Meteorology and Oceanography Center/Joint Typhoon Warning Center, processed using ArcGIS software.