Coping With Disaster: The Impact of Hurricanes on International Financial Flows, 1970-2002

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Abstract

How well do countries cope with the aftermath of natural disasters? In particular, do international financial flows help buffer countries in the wake of disasters? This paper focuses on hurricanes (one of the most common and destructive types of disasters), and examines the impact of hurricane exposure on resource flows to developing countries. Using meteorological data on storm paths, I construct a time-varying storm index that takes into account the fraction of a country's population exposed to storms of varying intensities. Across developing countries, greater hurricane exposure leads to large increases in foreign aid. For other types of international financial flows, the impact of hurricanes varies according to income level. In the poorer half of the sample, hurricane exposure leads to substantial increases in migrants' remittances, so that total inflows from all sources in the three years following hurricane exposure amount to roughly three-fourths of estimated damages. In the richer half of the sample, by contrast, hurricane exposure stimulates inflows of new lending from multilateral institutions, but offsetting declines in private financial flows are so large that the null hypothesis of zero damage replacement cannot be rejected.

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1 Introduction

Natural disasters cause tremendous losses of human life, as well as substantial economic damages. From 1970 to 2002, natural disasters killed an estimated 2.74 million people, injured another 2.70 million, and led to US$987 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 2002.

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 the impact of hurricanes, one of the most common and destructive types of disasters.[2] Wind storms, the disaster type that includes hurricanes, caused an estimated 612,000 deaths, 520,000 injuries, and US$280 billion in damages worldwide from 1970 to 2002.

A key contribution of this paper is to take a worldwide view in examining systematically the impact of hurricanes on international financial flows to developing countries. I examine several types of flows—official development assistance (ODA), lending from multilateral institutions, bank and trade-related lending, migrants' remittances, foreign direct investment, and portfolio investment—and estimate the responses of such flows to hurricane exposure, on average across all countries for which data are available. This topic has received only limited prior attention, typically consisting of studies of the impact of a small number of disasters in a limited set of countries (Albala-Bertrand 1993, Benson and Clay 2004).

Past analyses of the impact of hurricanes on international financial flows have been hampered by the lack of objective data on hurricane exposure at the country-year level. Data do exist on *damages* from storms, but such data are reported by national governments or other organizations and 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

[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'.

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 use of a time-varying storm index that takes into account the fraction of a country's population exposed to storms of varying intensities. The index is constructed using meteorological data on storm paths and intensities, combined with newly-available data on the subnational distribution of population. The index is highly predictive of disaster damages and human losses experienced by countries in particular years.

Across developing countries, greater hurricane exposure leads to large increases in foreign aid. For other types of international financial flows, the impact of hurricanes varies according to income level. In the poorer half of the sample, hurricane exposure also leads to substantial increases in migrants' remittances, and a slightly offsetting decline in bank and trade-related lending. For this poor-country subsample, instrumental variables estimates indicate that total inflows from all sources in the three years following hurricane exposure amount to roughly three-fourths of estimated damages. In the richer half of the sample, by contrast, hurricane exposure stimulates inflows of new lending from multilateral institutions, but offsetting declines in private financial flows are so large that the null hypothesis of zero damage replacement cannot be rejected.

This paper is part of a nascent 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. Anbarci, Escaleras, and Register (forthcoming) document that fatalities from earthquakes are greater in countries that are poorer and that have higher inequality. Bluedorn (2005) uses Caribbean hurricanes to test the intertemporal approach to current account determination. Bluedorn and Cascio (2005) study the impact of a hurricane in Puerto Rico on education and intergenerational mobility.[3]

Two highly related bodies of research are those on risk-coping mechanisms used by individual households in rural communities, on the one hand, and by countries, on the other. There is substantial microeconomic evidence on the methods used by households to cope with risk in developing countries. An empirical approach frequently taken is to examine how specific risk-coping mechanisms (such as transfer receipts, borrowing, asset sales, or savings accumulation or decumulation) respond to shocks. This paper shares this empirical approach. Studies frequently

[3]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.

document some ability to smooth consumption, but also find that there is far from complete smoothing (see, for example, Townsend (1995), Udry (1994), and Ligon, Thomas, and Worall (2002)).

On the other hand, research in international finance typically concludes that there is relatively little smoothing of national-level consumption via international risk-sharing arrangements or ex post smoothing mechanisms, such as French and Poterba (1991), Tesar (1993, 1995), Lewis (1996), and Van Wincoop (1999).[4] By contrast, this paper finds that specific types of international flows do respond positively to disaster events, replacing a large fraction of losses within a few years of a disaster. The difference between this paper's results and previous findings in international finance may reflect the fact that disasters are truly exogenous events, so that moral hazard problems that may inhibit the operation of consumption smoothing mechanisms in the face of other types of risks are not an issue for disasters.

Positive responses of international flows to hurricanes are likely to reflect a combination of both ex ante risk-sharing and ex post consumption smoothing. For example, the response of workers' remittances to disaster losses may be due to ex ante risk-sharing agreements via reciprocal transfers among relatives living in different countries. Transfers and credits from overseas individuals, governments, and institutions (appearing in the data as remittances, ODA, and lending from multilateral institutions) could also simply reflect desires, ex post, to assist those affected by disasters. On the other hand, if disasters lead to declines in expected rates of return or increases in risk perceptions, private asset sales (FDI, portfolio investment) and commercial credit could subsequently decline.

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.[5]

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

[4] However, there is evidence of risk-sharing and consumption smoothing within closely-tied economic regions such as states in the US and countries in the EU. See, for example, Asdrubali, Sorensen, and Yosha (1996) and Asdrubali and Kim (2004).

[5] Although see Yang and Choi (2005) for microeconomic study of the impact of local rainfall shocks in the Philippines on remittance inflows.

of international financial flows flows in sharing risk (in particular, disaster risk) across countries. Section 4 discusses relevant econometric issues and presents the empirical evidence. 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 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

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

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 from *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

In examining the impact of hurricanes on international financial flows, a focus on *storm damage* as the measure of hurricane "affectedness" would be problematic. Damage reports cannot plausibly be taken, in and of themselves, as exogenous with respect to the outcomes of interest. For example, reverse causation is likely to 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 instead focuses on a storm index created from objective meteorological data. Meteorological 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]

[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

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 prominently 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). I construct a storm index at the country-year level as follows.

The damage caused by hurricanes certainly depends on the intensity of the hurricane (in particular, windspeed). In addition, hurricanes should cause more damage if they strike in areas more highly concentrated in population. A storm index H_{jt} (for country j in year t) that takes such considerations into account is as follows:

$$H_{jt} = \frac{\sum_i \sum_s x_{isjt}}{N_{jt}}$$

where x_{isjt} is a measure of how affected a person i is by individual storm s in country j and year t. The measure of "affectedness" is the square of the windspeed above the tropical storm windspeed threshold (33 knots), normalized by the maximum of this variable. Specifically, x_{isjt} is:

$$x_{isjt} = \frac{(w_{isjt} - 33)^2}{(w^{MAX} - 33)^2}$$

w_{isjt} is the windspeed (in knots) to which an individual was exposed.[8] w^{MAX} is the maximum windspeed observed in the data, 152.3 knots. Individual affectedness is then summed across all storms in a given year and across all individuals in the country. It is then divided by population N_{jt} to obtain a per-capita measure.

The storm index can be thought of as *intensity-weighted events per capita*. If each of a country's residents were exposed to the maximum windspeed ($x_{isjt} = 1$ for all residents) on a single occasion in a single year, $H_{jt} = 1$ for that country in that year. Also, $H_{jt} = 1$ if each

are publicly accessible at http://weather.unisys.com/hurricane/index.html.

[8]A knot is one nautical mile per hour, and a nautical mile is 1.15 statute or land miles.

resident were exposed *twice* to a storm where $x_{isjt} = 0.5$.

While there is no data source for individual-level hurricane affectedness (x_{isjt}), it is possible to approximate the numerator in the formula for the storm index H_{jt}. First, I use available subnational estimates of population in a 0.25-degree-square worldwide grid.[9] Then, I estimate the windspeed experienced at each gridpoint due to each separate storm using the storm best-track data, a model of windspeed decay given distance from hurricane eyes (as in Dilley, et al 2005), and geographic information systems software. The summation then is across storms and across gridpoints (instead of individuals), with each gridpoint weighted by population. Because of inconsistent availability of windspeed data in initial years of data collection, I only construct this index for countries in South Asia (affected by North Indian Ocean storms) from 1979 and onwards, Oceania (South Pacific storms) from 1983 onwards, and Southern Africa (South Indian Ocean storms) from 1983 onwards. For storms in all remaining parts of the world (affected by West and East North Pacific and North Atlantic storms), windspeed data are available since the 1940s, so I construct the index for all years from 1970-2002.

Table 2 displays the mean storm index (for available years between 1970 and 2002 inclusive) for each country in a hurricane-affected region. The country with the highest mean storm index is the Philippines, with 0.0287, followed by the Dominican Republic (0.0205), Jamaica (0.0129), Haiti (0.0079), and Madagascar (0.0072).

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

[9]These data are from the Gridded Population of the World (GPW) dataset, described in Balk and Yetman (2004) and available at http://sedac.ciesin.columbia.edu/gpw.

any state of nature must be equal to a constant:

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

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:

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

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 $\overline{c}_{s_t}$:

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

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 exposure to 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. In addition, moral hazard problems that often inhibit the operation of insurance and other risk-coping arrangements should be much less of an issue for natural disasters: they are easily observable phenomena, and a country cannot affect its probability of being struck by one.

In practice, even if ex ante risk-sharing arrangements are incomplete, countries may also be able to use ex post mechanisms to smooth consumption, such as international borrowing and asset sales. Among others, Eaton and Gersovitz (1981), Kletzer (1984) and Grossman and Van

Huyck (1988) have underlined the function of sovereign debt as an ex post smoothing device.[10] Microeconomic studies have documented the role of asset sales as ex post smoothing devices, such as Rosenzweig and Wolpin (1993), Lim and Townsend (1998), and Fafchamps, Udry, and Czukas (1998). International transfers (ODA and remittances) may respond due to ex ante risk-sharing arrangements, as well as ex post responses by overseas individuals and governments with purely charitable motives. Microeconomic studies among households of the insurance and smoothing 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). In addition, inflows of new foreign direct investment could occur if asset destruction leads to increases in rates of return on investment. An increase in FDI due to an increase in the rate of return is different from other risk-sharing or consumption smoothing responses, but in practice it also helps in replacing lost assets. On the other hand, private asset sales (FDI, portfolio investment) and commercial credit could decline in the wake of disasters, if disasters lead to declines in expected rates of return or increases in perceived risk.

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:

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

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 (hurricane exposure).

The function of Pareto weights and the permanent income component $\widetilde{y}^i$ can be captured by a

[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.

country fixed effect γ_i. The mean world consumption level $\overline{c}_{s_t}$ can be represented by 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. Specifically, the net transfer measures will be net official development assistance, and net remittances from overseas migrants. Net borrowing will be lending from multilateral institutions as well as bank and trade-related private lending. And asset changes will be represented by net foreign direct investment and portfolio investment.

This paper will focus on a particular type of transitory shock $z^i_{s_t}$, hurricane exposure. 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 hurricane exposure. The empirical analysis will test the null hypothesis that the coefficient on inflows with respect to damages $z^i_{s_t}$ is equal to zero. In addition, the estimates will be used to shed light on the fraction of disaster damages that are replaced by international inflows (the "replacement rate" of damages by inflows).

4 Empirical evidence

This section documents the impact of hurricane exposure on international financial flows. I first describe other data sources used in the empirical analysis, and then describe summary statistics. The empirical results follow.

4.1 Other data sources

To examine the impact of hurricane exposure on disaster damages, I use 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.[11] These estimates are in currency units and 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

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

persist beyond the disaster year. I collapse these damage data to the country-year level. I also use data on number of people killed and injured 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 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* (ODA) is net bilateral disbursements of loans and grants made on concessional terms to promote economic development in developing countries, by members of the OECD's Development Assistance Committee (DAC). These figures include official aid to transition economies of Eastern Europe and the former Soviet Union. Both emergency aid sent in the immediate aftermath of disasters and aid intended for more long-term development initiatives are included in ODA. *Lending from multilateral institutions* is disbursements of loans and credits minus repayments of principal. I calculate the sum of WDI 2004's separately-reported net financial flows (both concessional and non-concessional) from the International Bank for Reconstruction and Development (IBRD), the International Development Association (IDA), the IMF, and regional development banks (such as the Inter-American Development Bank, the Asian Development Bank and the African Development Bank), and other multilateral lenders reported in the World Bank's Debtor Reporting System. *Bank and trade-related lending* includes commercial bank lending and other private credits. *Foreign direct investment* (FDI) 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.[12]

The following adjustments are made to these data. All figures reported in currency amounts

[12] 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.

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.

The sample for analysis includes developing countries with greater than one million population.[13] I also 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 2002 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 1,501 and 2,275 observations, depending on the outcome variable, and between 74 and 87 countries. The countries that actually experience hurricane exposure during the time period are those listed in Table 2 with a non-zero mean storm index. The remaining countries serve as controls, and primarily contribute to the estimates by improving the estimates of year fixed effects. The panel is unbalanced, with the number of observations varying across countries depending on data availability.

Table 3 presents summary statistics for the observations included in the analyses. Summary statistics for the storm index and storm damage are for all observations included in at least one international flow regression. The storm index has a mean of 0.0014 and a standard deviation of 0.0140. Disaster damage as a percentage of GDP has a mean of 0.73%, and the mean in levels is US$155 million. On average across country-year observations, 2.7 out of 100,000 inhabitants were killed due to storms. ODA as a share of GDP has a mean of 7.51%, but in some countries this figure is quite high: the 90th percentile of this variable is 18.69%. Other variables appear more evenly distributed worldwide. The mean of migrants' remittances as a share of GDP is 3.22%, with a 90th percentile of 7.92%. Mean lending from international institutions as a percentage

[13] I calculate mean population from 1968-1972, or in the earliest 5-year period available.

of GDP is 1.74%, and the corresponding means for bank and trade-related lending, FDI, and portfolio investment are 1.02%, 1.75%, and 0.18%, respectively.

4.2 Mean impact of hurricane exposure across countries

To assess the average impact of hurricane exposure on country-level outcomes, I estimate the following regression equation for an outcome Y_{jt} in country j and year t:

$$\begin{aligned} Y_{jt} &= \alpha_1 H_{jt} + \alpha_2 H_{jt-1} + \alpha_3 H_{jt-2} + \alpha_4 H_{jt-3} + \alpha_5 H_{jt-4} \\ &\quad + \gamma_j + \phi_t ASIA_j + \chi_t LAC_j + \omega_t AFR_j + \delta_j TREND + \varepsilon_{jt} \end{aligned} \tag{4}$$

H_{jt} is the storm index for country j and year t. Country fixed effects γ_j control for time-invariant differences across countries. Region-specific year effects ϕ_t, χ_t and ω_t allow for time-varying factors common to all countries in the same region ($ASIA_j$ is a dummy variable for Asia, LAC_j is a dummy variable for Latin America/Caribbean, and AFR_j is a dummy variable for Africa). $TREND$ is a linear time trend. Country-specific time trends (δ_j, the country-specific coefficient on 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 coefficients of interest, α_1 through α_5, are the impacts of the storm indices in the current year up to four years before (H_{jt} through H_{jt-4}) on current deviations from country-specific trends in the dependent variable.

Table 4, Panel A presents results for estimation of equation (4) where the dependent variables are the economic and human losses (as calculated from the EM-DAT database). Column 1 of the table presents results for a regression where the dependent variable is damage as a share of GDP. Greater hurricane exposure in the current year leads to higher storm damage. The coefficient on the storm index in the current year is positive and statistically significantly different from zero at the 5% level. The coefficient on the current-year storm index (0.376) indicates that a 0.1 increase in the storm index leads to storm damage amounting to 3.76 percent of GDP.

Columns 2 and 3 of the table present results for regressions where the dependent variables are number of people killed and number of people injured (respectively) as share of population. Greater hurricane exposure in the current year leads to greater proportions of population killed and injured. The coefficients on the year 0 storm index in the killed and injured regressions are statistically significantly different from zero at the 1% and 5% levels, respectively. The coefficients on the current-year storm indices in columns 2 and 3 indicate that a 0.1 increase in the storm index leads on average to an additional 0.8 people killed and 1.4 people injured per 1,000,000 population. In columns 1 through 3 all of the coefficients on the storm indices in years prior to the current year (years -1 to -4) are substantially closer to zero, indicating that the largest human and economic losses from storms tend to occur contemporaneously, rather than with a lag. However, there is some evidence of a lagged effect of storms on killed as fraction of population: the coefficient on the storm index in year -2 is positive and statistically significantly different from zero at the 5% level. Lagged effects of storms perhaps reflect the weakening of structures and disaster-recovery systems, so that losses from subsequent disasters are increased.

Subsequent results tables will present the impact of the mean storm index in years 0 to -3 on international financial flows.[14] So for comparison, Panel B of Table 4 presents the impact of the mean storm index in years 0 to -3 on the same outcome variables in Panel A, but where the outcome variables are now also defined as means in years 0 to -3. The coefficients on the mean storm index are statistically significantly different from zero (at the 5% level at least) for all three outcome variables, and each is somewhat larger than the year 0 coefficient in Panel A (because now both current and lagged effects of damages are captured).

Panel A of Table 5 presents results for regressions analogous to those in Panel A of Table 4, but where the outcomes of interest are various types of international financial flows: official development assistance (ODA), migrants' remittances, lending from multilateral institutions, bank and trade-related lending, foreign direct investment, and portfolio investment. The results in column 1 indicate that ODA inflows respond positively to hurricane exposure. In that column, the coefficients on the storm index in years -1 through -3 are positive and statisitically significantly different from zero (all at the 10% level). Lending from multilateral institutions also responds positively to hurricane exposure: the coefficients on the storm index in years -2 and -3 are positive and statisitically significantly different from zero at the 5% level. There is no evidence that, on

[14] This is simply the mean of the storm index in year 0 through year -3. In cases where the storm index is missing in one or more of these years, the mean is taken over the non-missing observations (for this reason, regressions in Panel B have slightly more observations than those in Panel A).

average across all countries, the other types of international financial flows respond positively to hurricane exposure. In columns 2, 4, 5, and 6 of the table, none of the coefficients on the current and lagged storm index variables are statistically significantly different from zero.

Because of the existence of lagged effects of hurricane exposure on international financial inflows, it is of interest to examine the relationship between the mean hurricane exposure in recent years on current financial flows. So Panel B of Table 5 presents regression results where the dependent variables are exactly as in Panel A, but where the independent variable of interest is the mean storm index in years 0 through -3. On average across all developing countries, mean hurricane exposure in years 0 to -3 causes inflows of official development assistance: the coefficient on the mean storm index in column 1 is positive and statistically significant at the 5% level. In each of the remaining columns, the coefficient on the mean storm index is always substantially smaller in magnitude than in the ODA regression (and sometimes negative) and is not statistically significantly different from zero.

4.3 Heterogeneity in impact of storms

The results in Tables 4 and 5 represent the mean impact of hurricane exposure across the developing countries in the dataset. It is also useful to understand heterogeneity in the effects of hurricane exposure that may be related to level of economic development, democratic institutions, international political connectedness to major donor countries, and geographic location.

The basic strategy is to interact the mean storm index in years 0 to -3 with variables representing each of these dimensions of heterogeneity. The level of economic development is simply per capita GDP in the initial period (the mean from 1968-1972), in thousands of 1995 US dollars.[15] Democratic institutions are represented by the Polity IV democracy index, which ranges from 0 to 10. Connectedness to major donor countries is measured by an index of the similarity of a country's international political alliances to those of the five largest contributors of foreign aid (USA, Japan, France, Britain, and Germany), as in Bueno de Mesquita and Lalman (1992), Bueno de Mesquita (1981), and Bueno de Mesquita (1985). Geographic location is captured simply by a Latin American dummy variable and an African dummy variable (Asia being the excluded category). Democratic institutions and alliance similarity are means in the 5-7 years prior to the observation in question.

Coefficient estimates on the mean storm index (years 0 to -3) and the associated interaction

[15] If data were not available on per capita GDP in 1968-1972, the mean was taken over the earliest subsequent 5-year period available.

terms are presented in Table 6.[16] In the first column, the dependent variable is mean disaster damage in years 0 to -3. None of the coefficient estimates on the interaction terms in that column are statistically significantly different from zero. There is no indication that there is important heterogeneity in the impact of hurricanes on disaster damage along these dimensions.

In the remaining columns of the table, the dependent variables are the six types of international financial flows previously examined. The most apparent pattern is that migrants' remittances respond less to hurricane exposure in richer countries: the coefficient on the per capita GDP interaction term is negative and statistically significantly different from zero at the 5% level. The interaction term with initial per capita income is also negative (but is not statistically significantly different from zero) in the other flow regressions. Another pattern that emerges (weakly) is that the coefficient on the democracy index interaction term is positive for all types of flows, but none of these interaction terms are statistically significant at conventional levels. There does not seem to be a strong pattern of heterogeneity related to alliance similarity: the interaction with alliance similarity takes on various signs across regressions, and is never statistically significantly different from zero.

To the extent there are regional differences in the impact of storms on international financial flows, they appear to be limited to Latin America. The Latin American interaction term is positive and statistically significantly different from zero (at the 10% level) in the regressions for bank and trade-related lending and for portfolio investment. The coefficient on the Latin American interaction term is also positive (but not statistically significant) in the regressions for remittances, lending from multilateral institutions, and FDI. The interaction term for Africa, on the other hand, shows no obvious pattern: the coefficient signs are both positive and negative, and none are statistically significantly different from zero.

4.4 Impact of hurricane exposure: richer vs. poorer countries

One of the most striking results in Table 6 was the negative coefficient on the interaction term between hurricane exposure and initial per capita GDP (particularly the statistically significant coefficient in the remittances regression). To further explore this particular dimension of heterogeneity, Table 7 presents the results from regressing international financial flows of various sorts on the mean storm index, for subsamples of the data separated at median initial per capita GDP

[16] Main effects for the democracy index and alliance similarity are also included in the regressions (coefficients not shown). Main effects for the other interaction terms do not need to be included as they would be absorbed by the country fixed effects.

(the full set of fixed effects and country-specific linear time trends remain in the regressions). Results for the richest half of countries are in Panel A, while those for the poorest half of countries are in Panel B.

In each panel, the coefficient on the mean storm index in years 0 to -3 is in the row labeled "Reduced form". In the reduced form coefficients in Panels A and B, the coefficient on the mean storm index in the ODA regression is positive and statistically significantly different from zero for both the richer and poorer subsamples (at the 10% and 5% levels, respectively). No other reduced form coefficient is statistically significantly different from zero in the subsample of richer countries, although the coefficients in the regressions for bank and trade-related lending and for FDI are actually negative and are not small in magnitude.

In the subsample of poorer countries (Panel B), the coefficient on the mean storm index in the remittances regression is also positive and is statistically significantly different from zero at the 1% level, while in the regression for bank and trade-related lending the coefficient is negative and statistically significantly different from zero at the 5% level.

To gauge the magnitude of the financial inflows vis-a-vis the damages caused, a row labeled "Instrumental variables (IV) estimates" presents coefficient estimates on mean damage as a share of GDP (in years 0 to -3), where damage is instrumented by the mean storm index in years 0 to -3. The first-stage and OLS (uninstrumented) regressions corresponding to the IV regressions are presented, respectively, in Appendix Tables 1 and 2.

In Appendix Table 1, each first-stage regression is accompanied by the F-statistic of the test of the null hypothesis that the coefficient on the instrument (mean storm index, years 0 to -3) is equal to zero. In first-stage regressions for the richer country subsample (Panel A of Appendix Table 1), the F-statistics range from 2.860 to 4.224, indicating that these are relatively weak instruments (according to critical values reported in Stock and Yogo 2005). Therefore, the IV results for the richer country subsample in Table 7 should be interpreted with caution.

By contrast, in the first-stage regressions for the poorer country subsample (Panel B of Appendix Table 1), the F-statistics are substantially larger, ranging from 25.101 to 135.751. Because these F-statistics substantially exceed the Stock and Yogo (2005) critical values, these are relatively strong instruments and the accompanying IV estimates therefore should have attractive size properties.

In Table 7, the coefficient on mean damage as share of GDP (in years 0 to -3) in the IV regressions should be interpreted as the fraction of damages replaced by the given type of international flow in the disaster year and the three years that follow (a "replacement rate"). In the richer subsample (results in Panel A), positive and statistically significant coefficients on the damage variable indicate that increases in damage lead to increases in ODA and lending from multilateral institutions. The point estimates indicate that 52.2 percent of damages are replaced by ODA, and 12.2 percent of damages are replaced by lending from multilateral institutions within three years following the damages. That said, the coefficients on damages for the remaining types of flows are all negative in sign, and the coefficients on bank and trade-related lending and on FDI are relatively large in magnitude (although none are statistically significantly different from zero).

In the poorer subsample (results in Panel B), the results indicate that increases in damage lead to increases in ODA and in migrants' remittances (coefficients on damage in these regressions are positive and statistically significant), but to declines in bank and trade-related lending (the coefficient in this regression is negative and statistically significant). There is little indication that other types of financial flows are affected by disaster damage in this poorer subsample: the coefficients on damage in the remaining regressions are all small in magnitude and none are statistically significantly different from zero.

5 Discussion: magnitudes of the results

How large are the estimated effects of hurricane exposure on international inflows? In particular, how large are the responses of *all international inflows combined* relative to the damages caused by hurricane exposure?

The replacement rate of disaster damages by some combination of international inflows is simply the sum of coefficients on mean damage across the corresponding IV regressions in of Table 7. Table 8 presents such sums of coefficients for various combinations of flows (and corresponding standard errors), separately for the richer and poorer country subsamples.

Of particular interest is the total replacement rate of disaster damages by all international inflows combined, the sum of the coefficients across columns 1 through 6. For the richer subsample, the replacement rate by all flows is 0.167, but this figure is very imprecisely estimated (the standard error is 0.507) so that the null hypothesis of zero replacement cannot be rejected. By contrast, for the poorer subsample, the replacement rate by all flows combined is 0.755 (roughly three-quarters), and this estimate is statistically significantly different from zero at the 5% level. Indeed, the null hypothesis of full replacement (a replacement rate of 1) cannot be rejected. All told, then, there is strong evidence that international inflows replace disaster damages for the poorer half of the sample, but not for the richer half.

Examining the replacement rate for subcategories of flows yields additional insights. When restricting attention to the two types of flows from "public" sources (the sum of ODA and lending from multilateral institutions), the replacement rate is positive and statistically significant for both the richer and poorer country subsamples (at the 1% and 10% levels, respectively). Strikingly, the estimated replacement rates are almost identical: 0.644 and 0.646 for the richer and poorer subsamples, respectively.

Suggestive evidence of differences across the subsamples emerges when considering private flows (the sum of remittances, bank and trade-related lending, FDI, and portfolio investment). For the richer subsample, the sum of coefficients is negative and large in magnitude (-0.477), while for the poorer subsample the sum is positive and small in magnitude (0.109). However, standard errors are large, so that neither sum is statistically significantly different from zero. It is apparently the large negative coefficient sum across private flows that leads the sum across all flows to be small in magnitude and statistically insignificant for the richer subsample.

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 the losses they experience in the wake of disasters. This paper fills this gap, focusing on hurricanes—one of the most common and destructive types of disasters.

Using meteorological data on storm paths, I construct a storm index at the country-year level that takes into account the fraction of a country's population exposed to storms of varying intensities. The analysis reveals striking differences across richer and poorer developing countries in the responsiveness of international financial flows to hurricane exposure. Across developing countries, greater hurricane exposure leads to large increases in foreign aid. For other types of international financial flows, the impact of hurricanes varies according to income level. In the poorer half of the sample, hurricane exposure also leads to substantial increases in migrants' remittances, and a slightly offsetting decline in bank and trade-related lending. For this poor-country subsample, instrumental variables estimates indicate that total inflows from all sources in the three years following hurricane exposure amount to roughly three-fourths of estimated damages. In the richer half of the sample, by contrast, hurricane exposure stimulates inflows of new lending from multilateral institutions, but offsetting declines in private financial flows are so large that the null hypothesis of zero damage replacement cannot be rejected.

A key result of this paper is that the response of official development assistance (foreign aid) to hurricane exposure is large in magnitude, and the size of the response does not differ greatly across countries with varying levels of economic development, democratic institutions, political connectedness to main donor countries, or geographic location. This result is perhaps surprising in light of evidence in Alesina and Dollar (2000) that political and strategic considerations have a large effect on bilateral foreign aid flows. There is no necessary contradition between the two papers, however. It very well may be that the *level* of foreign aid is influenced greatly by political and strategic factors, even if aid's *responsiveness to disasters* is not.

For other types of financial flows, this paper does document heterogeneity in responsiveness to disasters. The poorer the country, the more do migrants' remittances respond to hurricane exposure. This heterogeneity may be due to these countries' having larger migrant stocks in the developed world, migrant stocks that are more prone to remit, or both. Other private flows (commercial lending, FDI, and portfolio investment), actually decline in response to hurricane exposure, and the declines appear larger in the richer half of the sample (although estimates are too imprecise to make definitive statements). Declines in these other private flows following disasters may reflect declines in rates of return or increased risk perceptions on the part of international lenders and investors. However, these potential reasons behind heterogeneity in responsiveness of the various private flows are just hypotheses at this point. I consider understanding the reasons underlying heterogeneity in the impact of hurricane exposure on these private flows to be an important area for future research.

More generally, this paper provides the first evidence that some types of international financial flows help buffer countries from negative economic shocks. By contrast, related empirical work in international finance to date typically concludes that there is little cross-country risk-sharing and consumption smoothing. That said, this paper examines a specific kind of negative shock: losses due to natural disasters. A possible explanation for the divergence between this paper's results from the rest of the international finance research on the topic is that disasters are highly observable events, and that countries cannot influence the likelihood of experiencing one. Therefore, international risk-sharing and consumption smoothing mechanisms in the wake of disasters are not subject to moral hazard (unlike international mechanisms for dealing with, say, economic fluctuations driven by poor macroeconomic policy). 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 or droughts), to ascertain the generalizability of these results.

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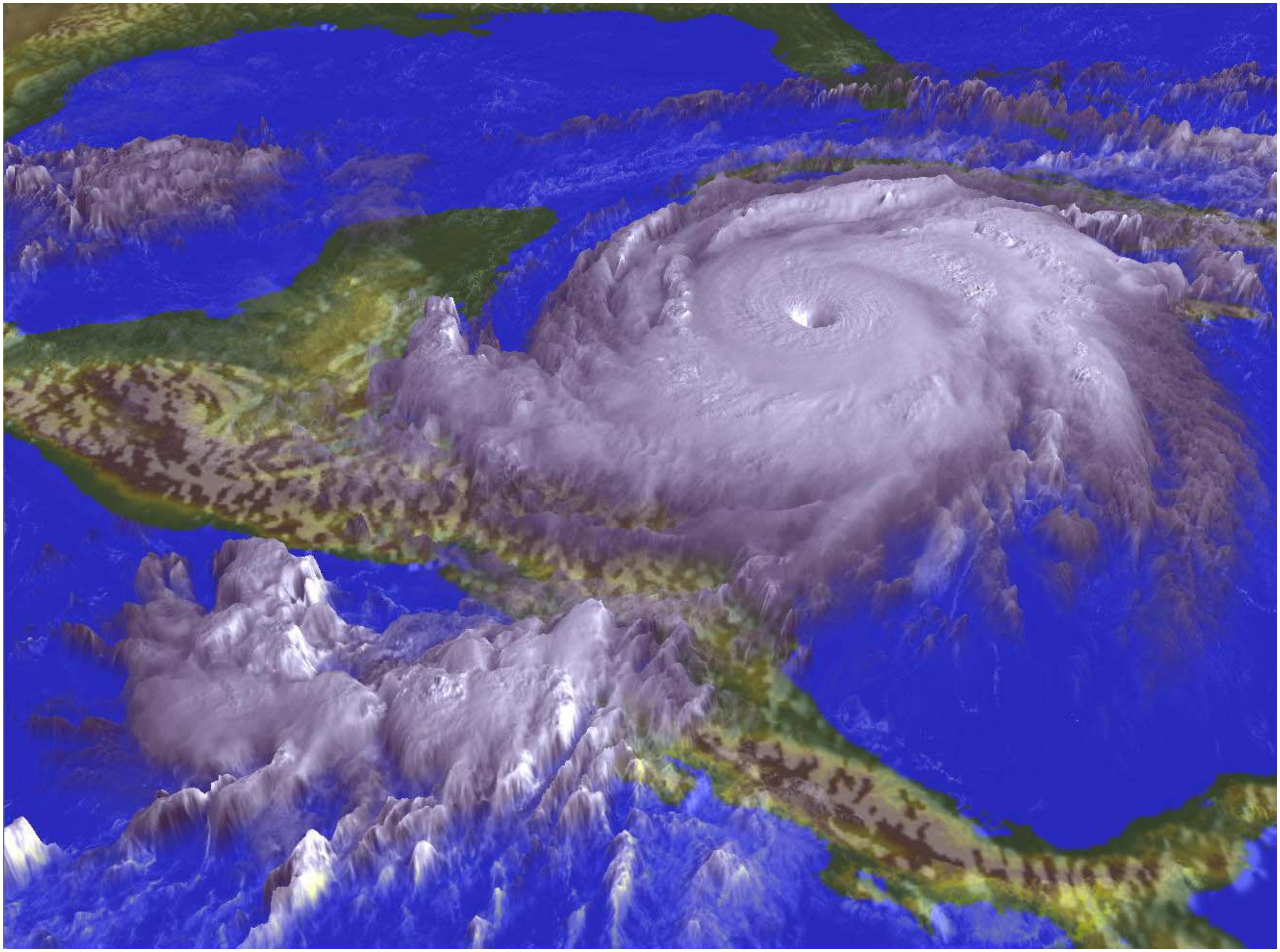
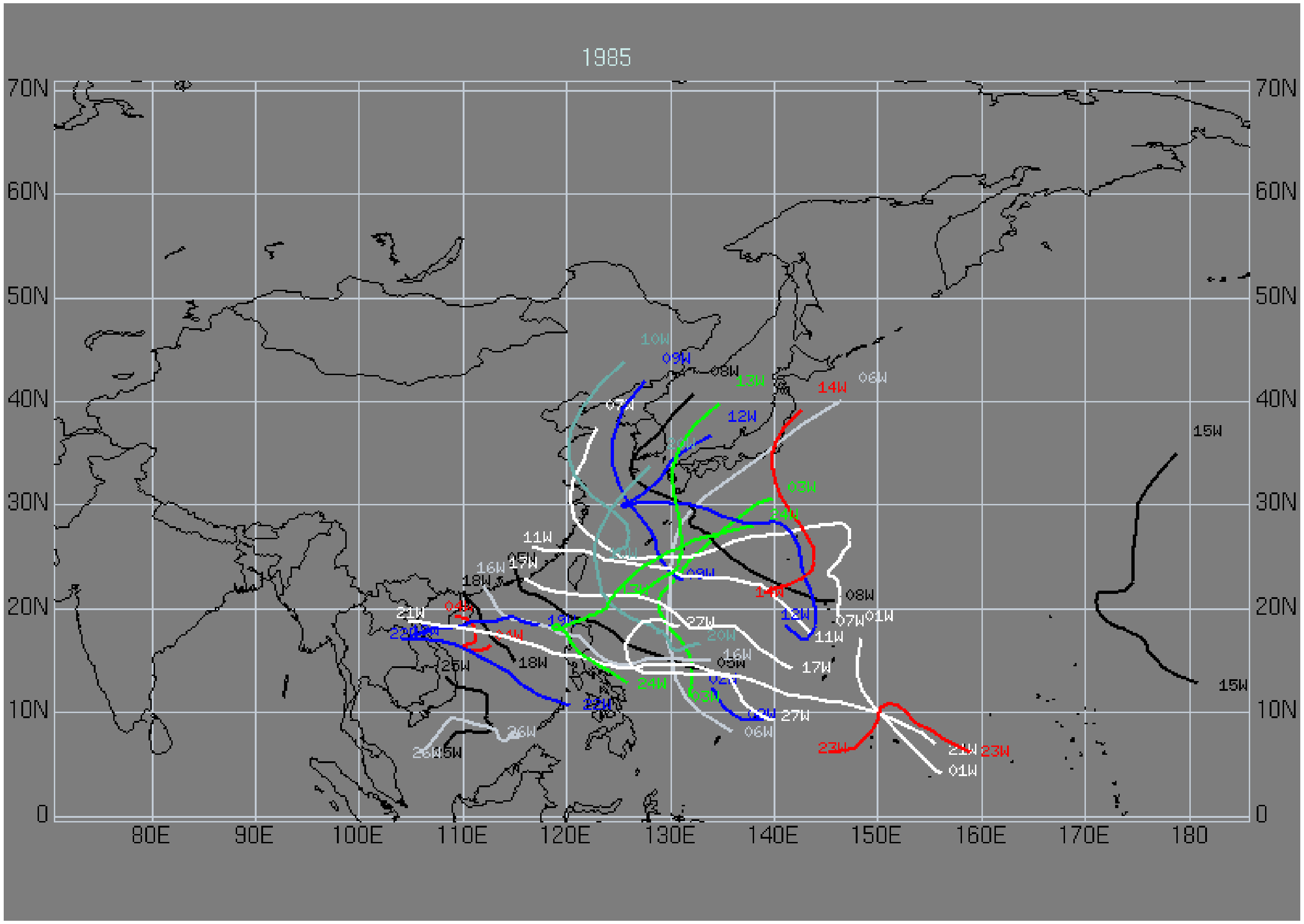
<u>Figure 1</u> Hurricane Mitch approaching Honduras, October 26, 1998



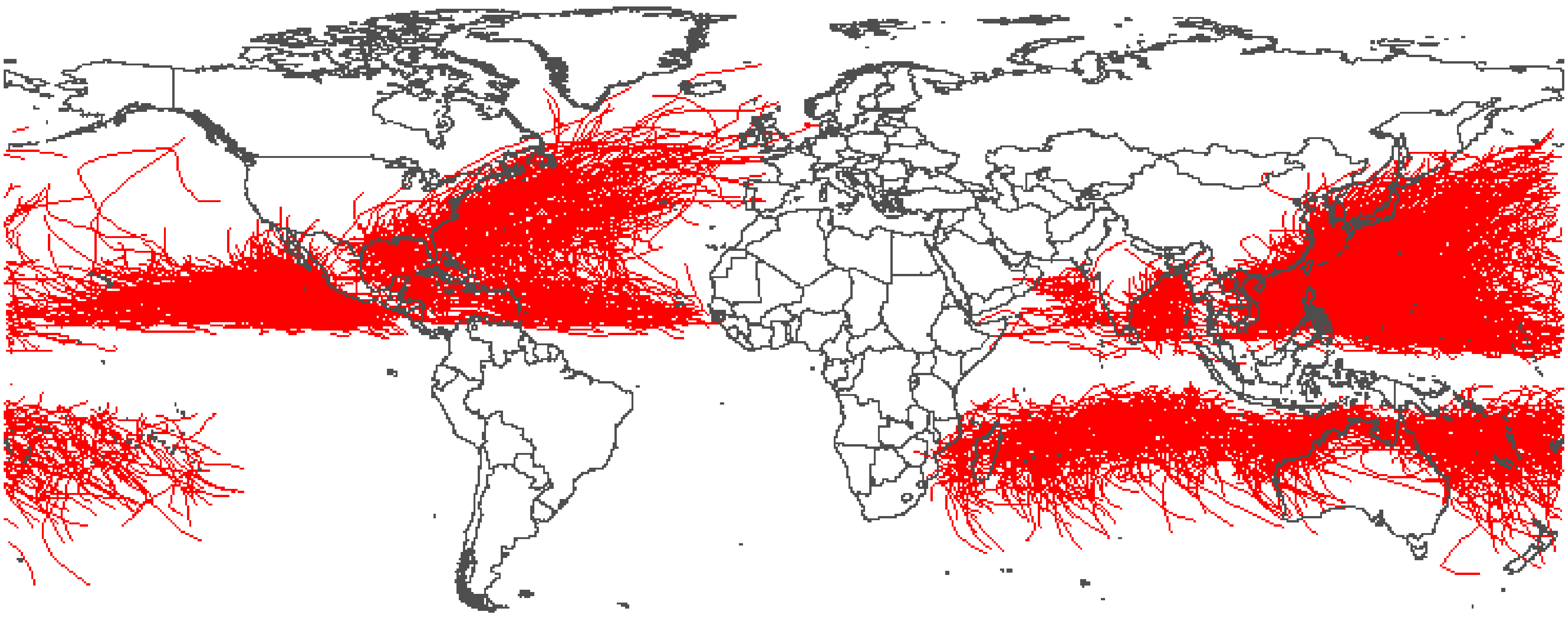
<u>Source</u>: http://rsd.gsfc.nasa.gov/rsd/images/Mitch.html.

<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, 1970-2002



<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.

Table 1: Human losses and damages from natural disasters worldwide 1970-2002

Type of disaster	Killed (000s)	Injured (000s)	Damage (1995 US$, 000s)	% of total damage
Drought	878	0	61,351,458	6.22%
Wind storm	612	520	280,019,414	28.38%
Earthquake	574	1,089	300,979,548	30.50%
Famine	232	0	71,798	0.01%
Flood	210	982	278,445,093	28.22%
Epidemic	154	80	1,450	0.00%
Volcano	26	8	5,514,201	0.56%
Earth slide	25	8	4,310,708	0.44%
Extreme temperature	21	10	27,589,390	2.80%
Wave / Surge	3	1	4,659	0.00%
Wild fire	1	2	28,244,056	2.86%
Insect infestation	0	0	251,002	0.03%
Total	2,737	2,701	986,782,776	100.00%

NOTES -- All figures are in thousands. Data are worldwide totals between 1970-2002 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.

<u>Table 2</u>: Mean storm index by country, 1970-2002

Region	Country	Mean storm index
Caribbean	Dominican Republic	0.020492
Caribbean	Jamaica	0.012867
Caribbean	Haiti	0.007932
Central America	Mexico	0.001487
Central America	Nicaragua	0.001431
Central America	Honduras	0.001130
Central America	Guatemala	0.000434
Central America	El Salvador	0.000025
Central America	Costa Rica	0.000001
Central America	Panama	0
East Asia	Korea, Rep.	0.004806
East Asia	China	0.001606
East Asia	Mongolia	0
Oceania	Papua New Guinea	0.000003
South Asia	Bangladesh	0.004568
South Asia	India	0.000784
South Asia	Sri Lanka	0.000308
South Asia	Pakistan	0.000159
South Asia	Nepal	0
Southeast Asia	Philippines	0.028723
Southeast Asia	Vietnam	0.006357
Southeast Asia	Myanmar	0.001354
Southeast Asia	Lao PDR	0.000413
Southeast Asia	Thailand	0.000080
Southeast Asia	Malaysia	0.000036
Southeast Asia	Cambodia	0.000022
Southeast Asia	Indonesia	0.000000
Southern Africa	Madagascar	0.007182
Southern Africa	Mozambique	0.001550
Southern Africa	Zimbabwe	0.000062
Southern Africa	Angola	0
Southern Africa	Lesotho	0
Southern Africa	Malawi	0
Southern Africa	South Africa	0
Southern Africa	Zambia	0

NOTES -- Rows of table sorted by region and mean storm index (mean over 1970-2002). Storm index is intensity-weighted events per capita in a given year, with squared windspeed as weight. Index is normalized: value of 1 means each inhabitant experiences a single hurricane at maximum windspeed observed over the time period. Sample of countries is developing countries with 1,000,000 or more population in 1968-1972. Hurricane data are from best track databases of the NOAA Tropical Prediction Center and the Naval Pacific Meteorology and Oceanography Center/Joint Typhoon Warning Center, processed using ArcGIS.

Table 3: Summary statistics, 1970-2002

	Mean	Std. Dev.	Minimum	10th pctile.	Median	90th pctile.	Maximum	Num. Obs.
Storm index, current year	0.0014	0.0140	0	0	0	0.00007	0.461	2,275
Disaster damage (% of GDP)	0.73%	6.62%	0.00%	0.00%	0.00%	0.49%	171.88%	2,275
Disaster damage (1995 US$, 000s)	154,773	1,017,566	0	0	0	142,052	20,670,939	2,275
Killed (% of population)	0.0027%	0.0282%	0%	0%	0.0001%	0.0024%	0.8227%	2,275
Injured (% of population)	0.0036%	0.0505%	0%	0%	0%	0.0011%	1.4679%	2,275
Official development assistance (% of GDP)	7.51%	9.35%	-0.78%	0.12%	3.97%	18.69%	96.13%	2,264
Migrants' remittances (% of GDP)	3.22%	10.24%	-10.39%	-1.11%	1.00%	7.92%	137.57%	1,501
Lending from multilateral institutions (% of GDP)	1.74%	2.41%	-5.91%	-0.11%	1.01%	4.71%	28.57%	2,163
Bank and trade-related lending (% of GDP)	1.02%	3.11%	-14.10%	-0.95%	0.05%	4.25%	34.99%	2,163
Foreign direct investment (% of GDP)	1.75%	3.61%	-30.32%	-0.02%	0.78%	5.04%	54.80%	1,761
Portfolio investment (% of GDP)	0.18%	3.26%	-58.41%	-0.33%	0.00%	1.24%	53.20%	1,742

NOTES-- The unit of observation is a country-year. Storm index is intensity-weighted events per capita in a given year, with squared windspeed as weight. Index is normalized: value of 1 means each inhabitant experiences a single hurricane at maximum windspeed observed over the time period. All international financial flows are net (inflows minus outflows); lending figures are new credits minus repayment of principal. 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.

Table 4: Impact of storms on economic and human losses, 1970-2002
(Fixed effects OLS estimates)

Panel A: Impact of storm index, years 0 to -4 separately

	(1)	(2)	(3)
Dependent variable:	Disaster damage as fraction of GDP	Killed as fraction of population	Injured as fraction of population
Coefficient on storm index:			
Year 0	0.376	0.000783	0.001356
	(0.156)**	(0.000202)***	(0.000582)**
Year -1	0.028	0.000174	0.000413
	(0.050)	(0.000130)	(0.000267)
Year -2	0.037	0.000174	0.000238
	(0.032)	(0.000087)**	(0.000225)
Year -3	-0.001	0.000223	-0.000127
	(0.023)	(0.000181)	(0.000407)
Year -4	-0.003	0.000073	0.000151
	(0.034)	(0.000111)	(0.000219)
Num. of obs.	2,227	2,227	2,227
R-squared	0.17	0.11	0.12

Panel B: Impact of mean storm index (years 0 to -3)

	(1)	(2)	(3)
Dependent variable (mean in years 0 to -3):	Disaster damage as fraction of GDP	Killed as fraction of population	Injured as fraction of population
Mean storm index, years 0 to -3	0.45	0.00116	0.001723
	(0.197)**	(0.000389)***	(0.000762)**
Num. of obs.	2,275	2,275	2,275
R-squared	0.52	0.3	0.3

* significant at 10%; ** significant at 5%; *** significant at 1%
NOTES -- Unit of observation is a country-year. Standard errors in parentheses, clustered by country. All regressions include country fixed effects, year-region fixed effects (regions are "Latin America/Caribbean", "Asia", and "Africa"), and country-specific linear time trends. Damage is divided by mean GDP 5-7 years before. Killed and injured in storms are divided by mean population 5-7 years before. See Table 3 for variable definitions and other notes.

Table 5: Impact of storms on international financial flows to developing countries, 1970-2002
(Fixed effects OLS estimates)

Panel A: Impact of storm index, years 0 to -4 separately

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable (share of GDP):	Official development assistance (ODA)	Migrants' remittances	Lending from multilateral institutions	Bank and trade-related lending	Foreign direct investment	Portfolio investment
Coefficient on storm index:						
Year 0	0.059	0.013	-0.005	-0.02	-0.034	-0.027
	(0.037)	(0.015)	(0.010)	(0.022)	(0.021)	(0.028)
Year -1	0.064	0.017	0.016	-0.028	-0.013	0.036
	(0.034)*	(0.019)	(0.011)	(0.023)	(0.014)	(0.039)
Year -2	0.094	0.014	0.014	-0.041	-0.018	-0.011
	(0.047)*	(0.015)	(0.006)**	(0.033)	(0.034)	(0.029)
Year -3	0.089	-0.015	0.03	-0.028	0.006	-0.008
	(0.050)*	(0.017)	(0.015)**	(0.023)	(0.038)	(0.025)
Year -4	0.042	-0.008	-0.003	0.001	0.031	0.034
	(0.028)	(0.014)	(0.012)	(0.027)	(0.039)	(0.039)
Num. of obs.	2,220	1,465	2,119	2,119	1,713	1,694
R-squared	0.84	0.96	0.61	0.42	0.64	0.28

Panel B: Impact of mean storm index (years 0 to -3)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable (share of GDP):	Official development assistance (ODA)	Migrants' remittances	Lending from multilateral institutions	Bank and trade-related lending	Foreign direct investment	Portfolio investment
Mean storm index, years 0 to -3	0.29	0.029	0.054	-0.115	-0.069	-0.022
	(0.144)**	(0.055)	(0.033)	(0.078)	(0.085)	(0.052)
Num. of obs.	2,264	1,501	2,163	2,163	1,761	1,742
R-squared	0.84	0.97	0.61	0.43	0.64	0.27

* significant at 10%; ** significant at 5%; *** significant at 1%
NOTES -- Unit of observation is a country-year. Standard errors in parentheses, clustered by country. All regressions include country fixed effects, year-region fixed effects (regions are "Latin America/Caribbean", "Asia", and "Africa"), and country-specific linear time trends. All dependent variables divided by mean GDP 5-7 years before. See Table 3 for variable definitions and other notes.

Table 6: Heterogeneity in impact of storms on international financial flows to developing countries, 1970-2002
(Fixed effects OLS estimates)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable (share of GDP):	Mean disaster damage, years 0 to -3	Official development assistance (ODA)	Migrants' remittances	Lending from multilateral institutions	Bank and trade-related lending	Foreign direct investment	Portfolio investment
Mean storm index, years 0-3	0.604	0.542	-0.399	0.263	-0.44	-0.537	-0.322
	(1.123)	(0.799)	(0.863)	(0.443)	(0.387)	(0.550)	(0.615)
(Mean storm index, years 0-3) x (Per capita GDP, 1968-1972, 000s of 1995 US$)	0.131	-0.031	-0.308	-0.118	-0.127	-0.023	-0.163
	(0.204)	(0.290)	(0.118)**	(0.123)	(0.117)	(0.189)	(0.098)
(Mean storm index, years 0-3) x (Polity IV democracy index, 5-7 years before)	0.05	0.045	0.035	0.04	0.04	0.028	0.023
	(0.051)	(0.064)	(0.032)	(0.034)	(0.026)	(0.046)	(0.026)
(Mean storm index, years 0-3) x (Alliance similarity with US, Japan, France, Britain, and West Germany, 5-7 years before)	-5.631	-2.631	4.889	-1.631	0.851	2.14	1.836
	(4.522)	(3.050)	(4.150)	(1.946)	(1.562)	(2.394)	(2.956)
(Mean storm index, years 0-3) x (Latin America dummy)	-0.021	-0.077	0.532	0.119	0.426	0.212	0.457
	(0.536)	(0.284)	(0.441)	(0.165)	(0.234)*	(0.247)	(0.260)*
(Mean storm index, years 0-3) x (Africa dummy)	-0.577	1.218	1.42	-0.458	0.656	-0.688	0.729
	(1.181)	(1.632)	(1.104)	(0.482)	(0.422)	(1.320)	(0.628)
Num. of obs.	2,111	2,100	1,419	1,999	1,999	1,647	1,636
R-squared	0.52	0.85	0.97	0.62	0.41	0.55	0.28

* significant at 10%; ** significant at 5%; *** significant at 1%
NOTES -- Unit of observation is a country-year. Standard errors in parentheses, clustered by country. All regressions include country fixed effects, year-region fixed effects (regions are "Latin America/Caribbean", "Asia", and "Africa"), and country-specific linear time trends. All dependent variables divided by mean GDP 5-7 years before. "Alliance similarity" captures extent to which country had similar international alliances with USA, Japan, France, Britain, and Germany. Polity IV democracy index ranges from 0 to 10 (10 is most democratic). Main effects for democracy index and alliance similarity also included in regressions (coefficients not shown). See Table 3 for variable definitions and other notes.

<u>Table 7</u>: Impact of storms and disaster damage on international financial flows, separately for richer and poorer developing countries

1970-2002
(Reduced form and IV estimates)

<u>Panel A: Countries above median initial per capita GDP</u>

	(1)	(2)	(3)	(4)	(5)	(6)
<u>Dependent variable (share of GDP)</u>:	Official development assistance (ODA)	Migrants' remittances	Lending from multilateral institutions	Bank and trade-related lending	Foreign direct investment	Portfolio investment
Reduced form:						
Coefficient on mean storm index, years 0 to -3	0.22	-0.013	0.052	-0.091	-0.058	-0.027
	(0.120)*	(0.060)	(0.035)	(0.082)	(0.098)	(0.064)
Num. of obs.	1,133	763	1,035	1,035	932	942
R-squared	0.81	0.91	0.45	0.52	0.71	0.29
Instrumental variables (IV) estimates:						
Coefficient on mean damage as share of GDP, years 0 to -3	0.522	-0.033	0.122	-0.214	-0.16	-0.07
	(0.098)***	(0.134)	(0.043)***	(0.287)	(0.359)	(0.150)
Num. of obs.	1,133	763	1,035	1,035	932	942

<u>Panel B: Countries at or below median initial per capita GDP</u>

	(1)	(2)	(3)	(4)	(5)	(6)
<u>Dependent variable (share of GDP)</u>:	Official development assistance (ODA)	Migrants' remittances	Lending from multilateral institutions	Bank and trade-related lending	Foreign direct investment	Portfolio investment
Reduced form:						
Coefficient on mean storm index, years 0 to -3	0.72	0.296	-0.025	-0.117	0.027	0.005
	(0.323)**	(0.109)***	(0.057)	(0.048)**	(0.087)	(0.032)
Num. of obs.	1,066	723	1,063	1,063	799	779
R-squared	0.82	0.98	0.66	0.36	0.49	0.34
Instrumental variables (IV) estimates:						
Coefficient on mean damage as share of GDP, years 0 to -3	0.669	0.198	-0.024	-0.108	0.016	0.003
	(0.351)*	(0.093)**	(0.054)	(0.033)***	(0.052)	(0.019)
Num. of obs.	1,066	723	1,063	1,063	799	779

* significant at 10%; ** significant at 5%; *** significant at 1%
NOTES -- Unit of observation is a country-year. Standard errors in parentheses, clustered by country. All regressions include country fixed effects, year-region fixed effects (regions are "Latin America/Caribbean", "Asia", and "Africa"), and country-specific linear time trends. All dependent variables divided by mean GDP 5-7 years before. Total number of observations across richer and poorer subsamples is lower than in previous tables because initial per capita GDP is not available for Myanmar. See Table 3 for variable definitions and other notes.

Table 8: Replacement rate of disaster damage by international financial flows, separately for richer and poorer developing countries
1970-2002

Panel A: Countries above median initial per capita GDP

	All flows	Flows from governments and international institutions (ODA, lending from multilateral institutions)	Flows from private sources (remittances, bank and trade-related lending, FDI, portfolio investment)
Replacement rate	0.167	0.644	-0.477
(Standard error)	(0.507)	(0.107)***	(0.495)

Panel B: Countries at or below median initial per capita GDP

	All flows	Flows from governments and international institutions (ODA, lending from multilateral institutions)	Flows from private sources (remittances, bank and trade-related lending, FDI, portfolio investment)
Replacement rate	0.755	0.646	0.109
(Standard error)	(0.373)**	(0.356)*	(0.111)

* significant at 10%; ** significant at 5%; *** significant at 1%
NOTES -- Replacement rates are inflows as fraction of disaster damages, calculated as sum of instrumental variables (IV) coefficients in Table 7 for corresponding flows.

Appendix Table 1: Impact of storms on disaster damage, separately for richer and poorer developing countries (first stage of IV regressions of Table 7)

1970-2002

(Fixed effects OLS estimates)

Panel A: Countries above median initial per capita GDP

Dependent variable: Mean damage in years 0 to -3 (as share of GDP)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample is observations with non-missing data on:	Official development assistance (ODA)	Migrants' remittances	Lending from multilateral institutions	Bank and trade-related lending	Foreign direct investment	Portfolio investment
Coefficient on mean storm index, years 0 to -3	0.422 (0.205)**	0.405 (0.205)*	0.426 (0.210)**	0.426 (0.210)**	0.366 (0.216)*	0.39 (0.200)*
F-stat: signif. of storm variable	4.224	3.923	4.115	4.115	2.860	3.776
P-value	0.046	0.056	0.05	0.05	0.098	0.059
Num. of obs.	1,133	763	1,035	1,035	932	942
R-squared	0.4	0.61	0.39	0.39	0.62	0.62

Panel B: Countries at or below median initial per capita GDP

Dependent variable: Mean damage in years 0 to -3 (as share of GDP)

	(1)	(2)	(3)	(4)	(5)	(6)
Sample is observations with non-missing data on:	Official development assistance (ODA)	Migrants' remittances	Lending from multilateral institutions	Bank and trade-related lending	Foreign direct investment	Portfolio investment
Coefficient on mean storm index, years 0 to -3	1.075 (0.215)***	1.498 (0.221)***	1.075 (0.214)***	1.075 (0.214)***	1.666 (0.150)***	1.693 (0.145)***
F-stat: signif. of storm variable	25.101	45.753	25.200	25.200	123.855	135.751
P-value	0.000	0.000	0.000	0.000	0.000	0.000
Num. of obs.	1,066	723	1,063	1,063	799	779
R-squared	0.65	0.84	0.65	0.65	0.72	0.74

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

NOTES -- Unit of observation is a country-year. Standard errors in parentheses, clustered by country. All regressions include country fixed effects, year-region fixed effects (regions are "Latin America/Caribbean", "Asia", and "Africa"), and country-specific linear time trends. See Table 3 for variable definitions and other notes.

Appendix Table 2: Impact of disaster damage on international financial flows, separately for richer and poorer developing countries (OLS analog to IV regressions of Table 7)

1970-2002

(Ordinary least-squares estimates)

Panel A: Countries above median initial per capita GDP

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable (share of GDP):	Official development assistance (ODA)	Migrants' remittances	Lending from multilateral institutions	Bank and trade-related lending	Foreign direct investment	Portfolio investment
Coefficient on mean damage as share of GDP, years 0 to -3	0.11	0.012	0.027	0.127	0.087	-0.034
	(0.041)**	(0.114)	(0.016)*	(0.060)**	(0.069)	(0.055)
Num. of obs.	1,133	763	1,035	1,035	932	942
R-squared	0.82	0.91	0.45	0.52	0.71	0.29

Panel B: Countries at or below median initial per capita GDP

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable (share of GDP):	Official development assistance (ODA)	Migrants' remittances	Lending from multilateral institutions	Bank and trade-related lending	Foreign direct investment	Portfolio investment
Coefficient on mean damage as share of GDP, years 0 to -3	0.127	-0.091	0.052	-0.007	0.018	-0.006
	(0.052)**	(0.043)**	(0.018)***	(0.013)	(0.058)	(0.014)
Num. of obs.	1,066	723	1,063	1,063	799	779
R-squared	0.82	0.98	0.66	0.35	0.49	0.34

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

NOTES -- Unit of observation is a country-year. Standard errors in parentheses, clustered by country. All regressions include country fixed effects, year-region fixed effects (regions are "Latin America/Caribbean", "Asia", and "Africa"), and country-specific linear time trends. All dependent variables divided by mean GDP 5-7 years before. See Table 3 for variable definitions and other notes.