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? Do international financial flows buffer countries in the wake of disasters? This paper examines the impact of hurricanes on resource flows to developing countries. Using meteorological data, I construct a time-varying storm index taking into account the fraction of a country's population exposed to storms of varying intensities. Overall, hurricanes lead to large increases in foreign aid. For other types of international financial flows, the impact of hurricanes varies according to income level. For poorer countries, hurricanes lead to increases in migrants' remittances, so that total inflows from all sources in the three years following hurricane exposure amount to roughly four-fifths of estimated damages. For richer countries, by contrast, hurricanes stimulate 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.

KEYWORDS: risk-sharing, insurance, official development assistance, foreign aid, remittances, foreign direct investment, international lending, natural disasters, hurricanes

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

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[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'.

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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.

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 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

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the three years following hurricane exposure amount to slightly more than four-fifths of estimated damages. In the richer half of the sample, by contrast, hurricane exposure stimulates inflows of new lending from multilateral institutions, but off-setting declines in private financial flows are so large that the null hypothesis of zero damage replacement cannot be rejected.

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.

To be sure, the international financial flows on which this paper focuses are complemented by a variety of other means by which countries cope with natural disasters, both prior to disasters (ex ante strategies) and after they occur (ex post strategies). Ex ante strategies include setting aside disaster-recovery funds in anticipation of a disaster (the country-level analog to household-level precautionary savings). Governments may also seek to reduce damages from future disasters by imposing zoning restrictions that strengthen building codes or discourage building; investing in public capital that mitigates the effects of disasters (such as levees to protect against floods); or requiring disaster insurance in disaster-prone areas. Kousky, Luttmer, and Zeckhauser (2006) theoretically examine the interactions between governments (who enact measures to protect against disasters) and private investors who locate in protected areas. Ex post, financial resources may also flow to disaster-affected areas from unaffected areas within the same political entity. Asdrubali, Sorensen, and Yosha (1996) and Asdrubali and Kim (2004) provide evidence of risk-sharing and consumption smoothing across closely-tied economic regions such as states in the US and countries in the EU.

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 (2005) 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 educa-

tion and intergenerational mobility.[3] Eisensee and Stromberg (2007) find that U.S.-provided relief for overseas disasters is driven by news coverage; aid is lower when news of disasters is overshadowed by other newsworthy events.

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 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). 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. This finding is significant, because of the moral hazard problem that generally exists in the context of insurance; insured countries could respond by underinvesting in disaster preparation, leading storms to have higher damages than if the country had not been insured. Knowing this, foreign individuals, firms, or governments might be less willing to provide post-disaster transfers.

The fact that I do find substantial international financial flows to disaster-affected countries may be because—as has been emphasized in the agricultural economics literature on weather-based index insurance—an insurance facility that conditions payouts on the occurrence of a quantifiable meteorological or natural event is not subject to one type of moral hazard: the policyholder cannot influence the likelihood of the insured event (Barnett and Mahul 2007, Chantarat et al. 2007). Countries cannot influence the likelihood of experiencing natural disasters (unlike, say, economic fluctuations driven by poor macroeconomic policy). If those making international transfers respond mainly to the occurrence of the natural event itself (rather than the actual damages incurred), this limits one aspect of the moral hazard problem. In addition, providers of international assistance may judge that certain countries may have little ability to engage in disaster-mitigation investments or self-

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[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.

insurance, so that there is in practice little moral hazard in this realm as well. The finding that overall financial flows respond more to storms in poorer countries than in richer ones may be seen as consistent with this hypothesis, if richer developing countries are thought to be better able to engage in self-insurance or *ex ante* disaster mitigation.

This paper's findings on the response of migrants' remittances to disaster damage also 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 using cross-national data until now.[4]

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 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.[5] 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

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[4]Although see Yang and Choi (2007) for a microeconomic study of the impact of local rainfall shocks in the Philippines on remittance inflows.

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

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 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.).

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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.
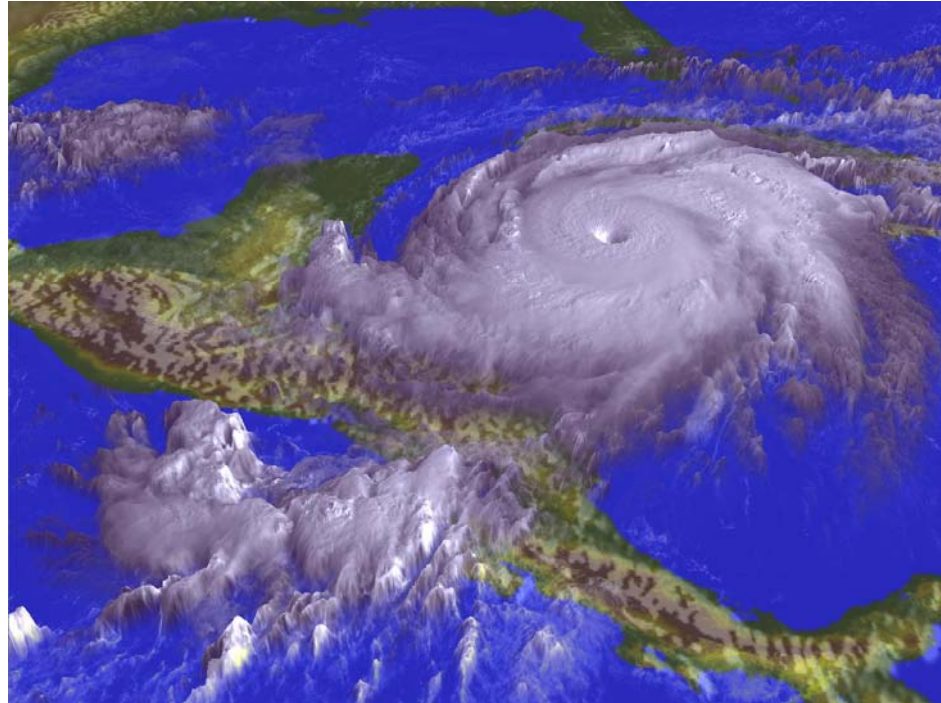
To deal with problems of reverse causation or omitted variables, this paper instead focuses on a storm index created from objective meteorological data. Meteorological data on hurricanes worldwide are available from two U.S. government agencies: the NOAA Tropical Prediction Center (for Atlantic and eastern 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).[6]

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 the 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:

$$H_{jt} = \frac{\sum\limits_{i} \sum\limits_{s} x_{isjt}}{N_{jt}}$$

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 wind-

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[6]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.

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Figure 2 **Western North Pacific best tracks, 1985**
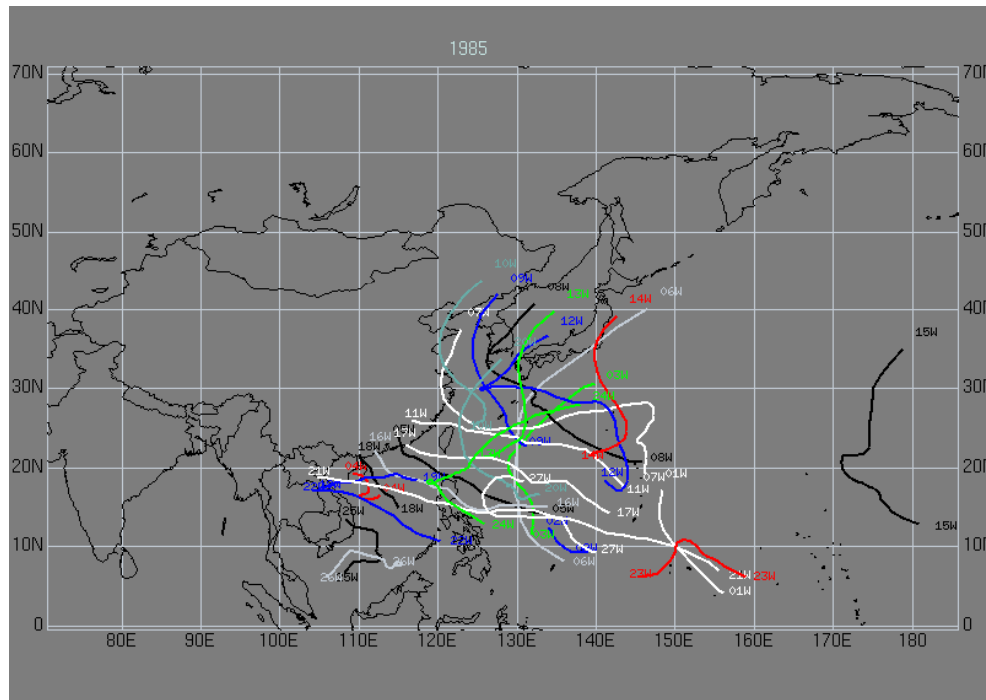
<u>Source</u>: Naval Pacific Meteorology and Oceanography Center/Joint Typhoon
Warning Center. Link provided in Chu et al (2002) and available at
<http://www.npmoc.navy.mil/jtwc/best_tracks/TC_bt_report.html>.

Figure 3 **Hurricane best tracks worldwide, 1970-2002**
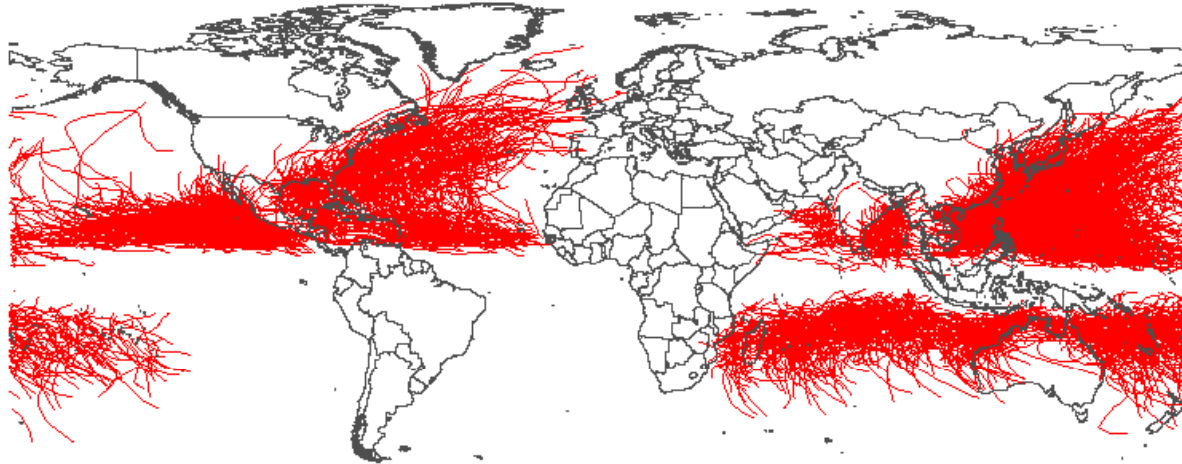
<u>Sources</u>: Hurricane best track databases of the NOAA Tropical Prediction Center and the Naval Pacific Meteorology and Oceanography Center/Joint Typhoon Warning Center, processed using ArcGIS software.

speed above the tropical storm windspeed threshold (33 knots), normalized by the maximum of this variable.[7] 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 resident were exposed *twice* to a storm where $x_{isjt} = 0.5$.[9]

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.[10] 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

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[7] The pressure exerted by winds on structures is typically modeled in climatology as rising in a squared (rather than a linear) term. See Emanuel (2005) and the references cited therein, among others.

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

[9] The storm index could be made more complicated by taking into account the amount of time a particular location has been exposed to the relevant winds. Due to the computational intensiveness of the calculation, the index does not incorporate such considerations. Moreover, the climatological literature does not devote great deal of attention to variation in the time that storms spend over particular locations. Indeed, the one study that computes an analogous storm index (Dilley et al 2005) also considers only wind speed, and not lateral (ground) speed of storms. The upshot is that not considering the ground speed of storms will be one source of measurement error in the storm index.

[10] 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.

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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 0.0370, followed by the Dominican Republic (0.0205), Jamaica (0.0128), 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, $y_{s_t}^i$, depending on the state of nature $s_t \in S$. A representative household in country i consumes $c_{s_t}^i$, and experiences within-period utility of $U_i\left(c_{s_t}^i\right)$ 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:

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

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

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

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Table 2: **Mean storm index by country, 1970-2002**

Region	Country	Mean storm index	In poorer subsample?
Caribbean	Dominican Republic	0.020492	
Caribbean	Jamaica	0.012787	
Caribbean	Haiti	0.007932	Y
Central America	Mexico	0.001487	
Central America	Nicaragua	0.001431	
Central America	Honduras	0.001130	Y
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	Y
East Asia	Mongolia	0	Y
Oceania	Papua New Guinea	0.000003	
South Asia	Bangladesh	0.004568	Y
South Asia	India	0.000784	Y
South Asia	Sri Lanka	0.000308	Y
South Asia	Pakistan	0.000159	Y
South Asia	Nepal	0	Y
Southeast Asia	Philippines	0.036997	
Southeast Asia	Vietnam	0.006357	Y
Southeast Asia	Myanmar	0.001354	Y
Southeast Asia	Lao PDR	0.000413	Y
Southeast Asia	Thailand	0.000080	Y
Southeast Asia	Malaysia	0.000036	
Southeast Asia	Cambodia	0.000022	Y
Southeast Asia	Indonesia	0.000000	Y
Southern Africa	Madagascar	0.007182	Y
Southern Africa	Mozambique	0.001550	Y
Southern Africa	Zimbabwe	0.000062	
Southern Africa	Angola	0	
Southern Africa	Lesotho	0	Y
Southern Africa	Malawi	0	Y
Southern Africa	South Africa	0	
Southern Africa	Zambia	0	Y

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. Inclusion in "poorer" subsample based on being at or below median of initial (1968-1972) per capita income ($1,943, nominal dollars); remaining countries are in "richer" subsample.

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 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.[11] 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 $\Delta a^i_{s_t}$:

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

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

So then we can rewrite equation (1) as:

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

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 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.

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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.[12] 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 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*

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[12]The dataset is maintained by the Center for Research on the Epidemiology of Disasters (CRED), Université Catholique de Louvain, and is available at <www.em-dat.net>.

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Table 3: Summary statistics, 1970-2002

	Mean	Std. Dev.	Minimum	10th pctile.	Median	90th pctile.	Maximum	Num. Obs.
Storm index, current year	0.0015	0.0147	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.

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.[13]

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.

The sample for analysis includes developing countries with greater than one million population.[14] 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 0.0015 and a standard deviation of 0.0147. Disaster damage as a percentage of GDP has a mean of 0.73%, and the mean in levels is US$155 million.

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[13]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.

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

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 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:

$$Y_{jt} = \alpha_1 H_{jt} + \alpha_2 H_{jt-1} + \alpha_3 H_{jt-2} + \alpha_4 H_{jt-3} + \alpha_5 H_{jt-4} \qquad (4)$$
$$+\gamma_j + \phi_t ASIA_j + \chi_t LAC_j + \omega_t AFR_j + \delta_j TREND + \varepsilon_{jt}$$

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

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	0.354	0.00074	0.001283
	(0.146)**	(0.000195)***	(0.000574)**
Year -1	0.022	0.000163	0.000387
	(0.054)	(0.000125)	(0.000256)
Year -2	0.039	0.000168	0.00023
	(0.031)	(0.000085)*	(0.000217)
Year -3	0	0.000207	-0.000121
	(0.022)	(0.000168)	(0.000382)
Year -4	0.003	0.000075	0.000148
	(0.037)	(0.000105)	(0.000209)
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	0.423	0.001102	0.001636
	(0.189)**	(0.000375)***	(0.000752)**
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.

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5% level. The coefficient on the current-year storm index (0.354) indicates that a 0.1 increase in the storm index leads to storm damage amounting to 3.54 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 0.7 people killed and 1.3 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.[15] 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 (at either the 5% or 10% level). Lending from multilateral insti-

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[15]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).

tutions also responds positively to hurricane exposure: the coefficients on the storm index in years -2 and -3 are positive and statistically significantly different from zero at the 5% level. There is no evidence that, on 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 the level of economic development, democratic institutions, international political connectedness to major donor countries, fraction of the country that is outside of hurricane-prone areas, and broad regional 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.[16] 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

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

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

Dependent variable (share of GDP):	(1) Official development assistance (ODA)	(2) Migrants' remittances	(3) Lending from multilateral institutions	(4) Bank and trade-related lending	(5) Foreign direct investment	(6) Portfolio investment
Coefficient on storm index:						
Year 0	0.057 (0.035)	0.012 (0.014)	-0.006 (0.010)	-0.02 (0.021)	-0.031 (0.021)	-0.028 (0.027)
Year -1	0.061 (0.032)*	0.014 (0.020)	0.014 (0.012)	-0.03 (0.023)	-0.012 (0.014)	0.041 (0.041)
Year -2	0.09 (0.044)**	0.014 (0.015)	0.013 (0.007)**	-0.042 (0.031)	-0.019 (0.033)	-0.012 (0.028)
Year -3	0.085 (0.046)*	-0.014 (0.017)	0.029 (0.014)**	-0.027 (0.022)	0.008 (0.037)	-0.011 (0.027)
Year -4	0.042 (0.027)	-0.005 (0.016)	-0.002 (0.012)	-0.001 (0.026)	0.029 (0.037)	0.042 (0.045)
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)

Dependent variable (share of GDP):	(1) Official development assistance (ODA)	(2) Migrants' remittances	(3) Lending from multilateral institutions	(4) Bank and trade-related lending	(5) Foreign direct investment	(6) Portfolio investment
Mean storm index, years 0 to -3	0.277 (0.133)**	0.026 (0.053)	0.049 (0.033)	-0.116 (0.074)	-0.065 (0.081)	-0.027 (0.053)
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.

alliance similarity are means in the 5-7 years prior to the observation in question.

The fraction of a country that is not hurricane-prone is an interesting interaction term to consider because countries that have most of their land masses outside of hurricane-prone areas may have more opportunities to substitute internal financial flows for international ones. This is measured simply as the fraction of the country that is outside of hurricane-prone latitudes. Hurricane-prone latitudes are those between 5 and 23.5 degrees north latitude or between 5 and 23.5 degrees south latitude.[17]

Coefficient estimates on the mean storm index (years 0 to -3) and the associated interaction terms are presented in Table 6.[18] In the first column, the dependent

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[17]23.5 degrees north (south) latitude is the northern (southern) boundary of the tropics, where hurricanes typically form and are strongest. 5 degress north (south) latitude is a relevant boundary because the earth's coriolis force is too weak closer the equator to allow hurricane formation or persistence (Alexander 1993).

[18]Main effects for the democracy index and alliance similarity are also included in the regressions

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

Dependent variable (share of GDP):	(1) Mean disaster damage, years 0 to -3	(2) Official development assistance (ODA)	(3) Migrants' remittances	(4) Lending from multilateral institutions	(5) Bank and trade-related lending	(6) Foreign direct investment	(7) Portfolio investment
Mean storm index, years 0-3	0.195 (0.925)	0.106 (0.720)	-0.774 (0.644)	-0.11 (0.476)	-0.855 (0.385)**	-0.582 (0.493)	-0.497 (0.656)
(Mean storm index, years 0-3) x (% of land mass in outside of hurricane-prone latitudes)	0.687 (1.387)	1.029 (0.543)*	0.919 (0.782)	1.092 (0.821)	1.602 (1.016)	0.037 (0.710)	0.291 (0.766)
(Mean storm index, years 0-3) x (Per capita GDP, 1968-1972, 000s of 1995 US$)	0.173 (0.165)	0.02 (0.234)	-0.263 (0.100)**	-0.056 (0.106)	-0.067 (0.112)	0.033 (0.158)	-0.129 (0.088)
(Mean storm index, years 0-3) x (Polity IV democracy index, 5-7 years before)	0.037 (0.040)	0.031 (0.048)	0.022 (0.027)	0.022 (0.029)	0.023 (0.023)	0.014 (0.037)	0.012 (0.024)
(Mean storm index, years 0-3) x (Alliance similarity with US, Japan, France, Britain, and West Germany, 5-7 years before)	-4.087 (3.821)	-1.221 (2.888)	6.379 (3.229)*	0.024 (2.097)	2.912 (1.444)**	2.092 (2.121)	2.804 (3.236)
(Mean storm index, years 0-3) x (Latin America dummy)	0.172 (0.398)	0.142 (0.224)	0.69 (0.317)**	0.234 (0.168)	0.541 (0.184)***	0.175 (0.210)	0.485 (0.260)*
(Mean storm index, years 0-3) x (Africa dummy)	-0.238 (0.956)	1.531 (1.590)	1.693 (0.887)*	-0.216 (0.452)	0.889 (0.321)***	-0.724 (1.293)	0.846 (0.620)
Num. of obs.	2,110	2,099	1,418	1,998	1,998	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. "Hurricane-prone latitudes" are between 5 and 23.5 degrees north latitude and between 5 and 23.5 degrees south latitude. "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.

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. 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. Another pattern that emerges is that the coefficient on the alliance similarity interaction term is positive for remittances and bank and trade-related lending, at the 10% and 5% significance levels, respectively. Both the Latin America and Africa interaction terms are positive and statistically significantly different from zero in the regressions for bank and trade-related lending and for remittances. The interaction term with the percentage of land area outside of hurricane-prone latitudes is statistically significantly different from zero (at the 10% level) in the ODA regression, and is positive in sign. This latter result may reflect omitted variables related to geographic or cultural proximity to donor nations.

A question that arises is whether the larger remittance response on the part of poor countries simply is due to poor countries having more international migrants. In addressing this question, the starting point should be panel data on the stock of international migrants for each remittance-destination country. Unfortunately, such data are not available, so instead I constructed a proxy for the migrant stock using panel data on migration flows: the cumulative number of migrants reported as having entered a range of high-income OECD countries over a prior 10-year period. While this is an imperfect proxy for the migrant stock, in some ways it may better capture the phenomenon of interest if more recent migrants are more likely to send remittances than migrants who have been away longer.[19]

I test whether countries that are hit by hurricanes receive higher remittance flows when they have larger overseas migrant stocks by including in a regression analogous to that of Table 6's column 3 (where the dependent variable is migrant remittances) an interaction term between the storm index and international migrants as a share of the country's population.[20] Of interest is what effect inclusion of

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(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.

[19] The data on migration flows is contained in a dataset assembled by the UN Population Division, "International Migration Flows to and from Selected Countries: The 2005 Revision". The dataset consists of annual data on reported legal entries of migrants to 15 high-income OECD countries from every other country in the world for the past several decades.

[20] I calculate the cumulative total of international migrants reported as entering 15 OECD countries from 5 to 14 years prior to the observation in question. The migrant stock variable has a mean

this additional interaction term has on the coefficient on the interaction term with per capita GDP. If the negative coefficient on the interaction term with per capita GDP reported in regression 3 of Table 6 is simply due to poorer countries' having larger migrant stocks, inclusion of the interaction term with the migrant stock should cause the coefficient on the interaction term with per capita GDP to become smaller in magnitude.

As it turns out, the coefficient on the storm index/migrant stock interaction term (3.17), while positive, is not statistically significantly different from zero (the standard error is 7.96). There is no support for the hypothesis that remittance responses to storms are higher in countries with larger migrant stocks. In addition, the coefficient on the interaction term with per capita GDP does not decline in magnitude vis-à-vis the corresponding coefficient in regression 3 of Table 6. In fact, the coefficient actually becomes slightly larger in absolute value (-0.338 instead of -0.263), and it remains statistically significant at the 10% level. The higher response of remittances to storms among poorer countries appears not to be due to their simply having larger migrant stocks. While this is just speculation, it may that households exposed to hurricanes in poorer countries are less able to smooth consumption via other means (such as by taking out loans or drawing upon formal savings), and so rely more on their international migrant relatives for remittances in coping with shocks.

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 (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.[21]

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

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of 0.006 and a standard deviation of 0.013. I use the lagged migrant stock to alleviate concerns about endogeneity of the migrant stock to hurricanes. Results are essentially the same if I use the cumulative total entries from 1 to 10 years prior to the year in question as the proxy for migration.

[21]Median initial per capita GDP in the 1968-1972 period (averaged across those years for each country) was US$1,943 (in nominal dollars). Richer countries are defined as those with incomes above that cutoff, and poor countries those with incomes equal to or below that cutoff.

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

1970-2002
(Reduced form and IV 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
Reduced form:						
Coefficient on mean storm index, years 0 to -3	0.21 (0.112)*	-0.013 (0.057)	0.049 (0.035)	-0.085 (0.081)	-0.053 (0.095)	-0.033 (0.065)
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	0.525 (0.103)***	-0.034 (0.135)	0.12 (0.050)**	-0.21 (0.286)	-0.153 (0.355)	-0.089 (0.165)
Num. of obs.	1,133	763	1,035	1,035	932	942

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
Reduced form:						
Coefficient on mean storm index, years 0 to -3	0.8 (0.336)**	0.297 (0.109)***	-0.003 (0.054)	-0.134 (0.053)**	0.026 (0.083)	0.003 (0.033)
Num. of obs.	1,098	738	1,095	1,095	815	795
R-squared	0.82	0.98	0.66	0.35	0.49	0.34
Instrumental variables (IV) estimates:						
Coefficient on mean damage as share of GDP, years 0 to -3	0.732 (0.348)**	0.2 (0.095)**	-0.003 (0.049)	-0.123 (0.039)***	0.016 (0.050)	0.002 (0.020)
Num. of obs.	1,098	738	1,095	1,095	815	795

* 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.

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 2.91 to 4.27, 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 28.16 to 134.54. 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 52.5 percent of damages are replaced by ODA, and 12.0 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.[22]

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[22]One might be interested in whether there is nonlinearity in the impact of (instrumented) damage on the various financial flows. There is no evidence that this type of nonlinearity is present. In

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5   Discussion and extensions

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 0.159, but this figure is very imprecisely estimated (the standard error is 0.511) 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 0.824, 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 very similar: 0.645 and 0.729 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 (-0.486), while for the poorer subsample the sum is positive and small in magnitude (0.095). 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.

Given these differences in the degree to which international financial flows 're-place' damages, it is reasonable to ask how household *consumption* varies with

analogous regressions where I instrument for both damage and its square with the storm index and its square (not shown but available from author on request), in no case is the instrumented squared damage term statistically significantly different from zero.

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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	0.159	0.645	-0.486
(Standard error)	(0.511)	(0.114)***	(0.498)

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	0.824	0.729	0.095
(Standard error)	(0.371)**	(0.353)**	(0.113)

* 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.

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current and lagged storm exposure across richer and poorer countries. Appendix Table 3 presents regressions analogous to those of Table 5, where the dependent variable is household final consumption expenditure (also as a share of mean GDP 5-7 years before) from the World Development Indicators dataset. In column 1, the sample is all countries, while in columns 2 and 3 the samples are the richer and poorer subsets as previously defined. Panel A presents regressions examining the effects of storms in the current year and up to four years of lags, while Panel B presents the effect of the mean storm index from years 0 to -3. Overall, there is little evidence of a statistically significant relationship between current or lagged storms and household final consumption for any of the samples. This may indicate that a combination of international financial flows and countries' internal risk-coping mechanisms is sufficient to keep consumption stable in the wake of hurricanes. The exception is the negative coefficient on the 4-year-lagged storm index for the poorer country subsample. While this coefficient is only significant at the 10% level (and so may simply reflect sampling variation), one possible explanation is that the international financial flows that are important for consumption smoothing for poorer countries have diminished substantially by the 4th year after a hurricane.

The analysis so far has focused on international financial inflows up to three years after storm exposure, which is an important time window if one is concerned about countries' abilities to cope in the immediate aftermath of disasters. But it is also important to ask whether increases in inflows after a disaster are simply a 're-timing' of flows that would have occurred anyway, but at a later date: are inflows in the immediate wake of a disaster offset by declines in a later year? If so, then while disaster-related inflows may help with short-term consumption smoothing, they would not represent net transfers to affected countries when looking over some longer time-frame.

Regression analysis in Appendix Tables 4 and 5 investigate this question. For the richer and poorer subsamples, Appendix Tables 4 and 5 (respectively) present results from regressions where the dependent variable is a specific financial flow, and the key independent variables are the current storm index and up to 7 lags of the storm index, for 8 storm indices in total. 'Re-timing' of flows would take the form of shifts in the sign of the storm index coefficients as one moved from shorter to longer lags (for example, positive coefficients at shorter lags, and negative coefficients at longer lags). I also add up coefficients across contiguous years to get a sense of the cumulative impact of a given level of storm exposure across those years (for example, adding up coefficients across years 0 to-3 gives the total effect of storm exposure up to three years after a storm), and these coefficient sums (and statisical significance levels) are reported at the bottom of the tables.

Overall, there is mixed evidence of re-timing of flows across the richer and poorer subsamples and across the types of flows. For ODA inflows to the richer

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subsample, there is no evidence of re-timing of flows up to 7 years after storm exposure. Rich country ODA inflows are positively affected by storm exposure up to 6 years after storm exposure (the coefficient on year -6 is positive and statistically significant). The sum of coefficients across years 0 to -7 is positive and statistically significantly different from zero, as is the sum across the subperiods 'years 0 to -3' and 'years -4 to -7'. In the richer subsample, there also does not appear to be retiming of lending from multilateral institutions (the sum of coefficients in years -4 to -7 is near zero and not statistically significant).

There also does not appear to be re-timing for remittance flows to the poorer countries. The sum of coefficients on the storm index is positive across years 0 to -3 and statistically significantly different from zero. For years -4 to -7, the sum of coefficients, while negative, is much smaller in magnitude and is not statistically significantly different from zero, indicating little evidence of offsetting declines in remittances in that time window. (It is true that the sum of coefficients across years 0 to -7 is not statistically significantly different from zero, but this is simply due to a substantial increase in the standard error of the linear combination of the coefficients; the point estimate across years 0 to -7 is little different from the coefficient across years 0 to -3.)

On the other hand, there appears to be evidence of re-timing for ODA flows to poorer countries. While the sum of coefficients across years 0 to -3 (column 1 of Appendix Table 5) is positive and statistically significantly different from zero (at the 10% level), the coefficient sum across years -4 to -7 is negative, statistically significant, and not small in magnitude. As a result, the sum of coefficients across years 0 to -7, while positive, is only about a third as large as the sum across years 0 to -3 and is not statistically significantly different from zero.

The difference across rich and poor countries in the re-timing of ODA flows is striking. One might speculate that the difference is due to relatively weak lobbying or bargaining power on the part of poorer countries, so disaster relief for richer developing countries constitute truly new resources, while disaster relief for poorer nations simply shift later flows earlier in time. This difference is likely to deserve further investigation in subsequent research.

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 four-fifths 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 is 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.

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 contradiction 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. 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. 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. In addition, valuable future work could use an analogous instrumental variables approach to understand the

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impact of damages from other types of disasters (such as earthquakes or droughts), to ascertain the generalizability of these results.

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)

Sample is observations with non-missing data on:	(1) Official development assistance (ODA)	(2) Migrants' remittances	(3) Lending from multilateral institutions	(4) Bank and trade-related lending	(5) Foreign direct investment	(6) Portfolio investment
Coefficient on mean storm index, years 0 to -3	0.4 (0.193)**	0.384 (0.194)*	0.404 (0.197)**	0.404 (0.197)**	0.347 (0.203)*	0.369 (0.189)*
F-stat: signif. of storm variable	4.27	3.92	4.19	4.19	2.91	3.81
P-value	0.045	0.056	0.048	0.048	0.095	0.058
Num. of obs.	1,133	763	1,035	1,035	932	942
R-squared	0.4	0.61	0.39	0.39	0.62	0.61

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

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

Sample is observations with non-missing data on:	(1) Official development assistance (ODA)	(2) Migrants' remittances	(3) Lending from multilateral institutions	(4) Bank and trade-related lending	(5) Foreign direct investment	(6) Portfolio investment
Coefficient on mean storm index, years 0 to -3	1.093 (0.206)***	1.484 (0.221)***	1.092 (0.205)***	1.092 (0.205)***	1.663 (0.150)***	1.691 (0.146)***
F-stat: signif. of storm variable	28.16	44.90	28.25	28.25	123.47	134.54
P-value	0.000	0.000	0.000	0.000	0.000	0.000
Num. of obs.	1,098	738	1,095	1,095	815	795
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

Dependent variable (share of GDP):	(1) Official development assistance (ODA)	(2) Migrants' remittances	(3) Lending from multilateral institutions	(4) Bank and trade-related lending	(5) Foreign direct investment	(6) Portfolio investment
Coefficient on mean damage as share of GDP, years 0 to -3	0.11 (0.041)**	0.012 (0.114)	0.027 (0.016)*	0.127 (0.060)**	0.087 (0.069)	-0.034 (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

Dependent variable (share of GDP):	(1) Official development assistance (ODA)	(2) Migrants' remittances	(3) Lending from multilateral institutions	(4) Bank and trade-related lending	(5) Foreign direct investment	(6) Portfolio investment
Coefficient on mean damage as share of GDP, years 0 to -3	0.13 (0.054)**	-0.09 (0.043)**	0.053 (0.018)***	-0.007 (0.013)	0.019 (0.058)	-0.006 (0.014)
Num. of obs.	1,098	738	1,095	1,095	815	795
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.

Appendix Table 3: Impact of storms on international financial flows to developing countries, 1970-2002
(Fixed effects OLS estimates)

<u>Dependent variable:</u> Household final consumption expenditure

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

	(1)	(2)	(3)
<u>Sample:</u>	All countries	Richer countries	Poorer countries
Coefficient on storm index:			
Year 0	-0.032	-0.122	0.245
	(0.174)	(0.136)	(0.307)
Year -1	0.01	-0.084	0.138
	(0.186)	(0.158)	(0.310)
Year -2	0.005	-0.066	-0.327
	(0.228)	(0.200)	(0.312)
Year -3	0.068	0.003	0.03
	(0.215)	(0.193)	(0.349)
Year -4	0.122	0.096	-0.219
	(0.159)	(0.147)	(0.114)*
Num. of obs.	2,091	1,085	1,006
R-squared	0.74	0.73	0.75

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

	(1)	(2)	(3)
<u>Sample:</u>	All countries	Richer countries	Poorer countries
Mean storm index, years 0 to -3	-0.002	-0.309	-0.072
	(0.718)	(0.594)	(0.754)
Num. of obs.	2,139	1,097	1,042
R-squared	0.75	0.73	0.77

* 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. Dependent variables divided by mean GDP 5-7 years before. See Table 3 for other notes. Richer and poorer country samples split (as in Table 7) at median initial (1968-1972) per capita GDP.

Appendix Table 4: Impact of storms on international financial flows to developing countries, 1970-2002
Countries above median initial per capita GDP
(Fixed effects OLS estimates)

Dependent variable (share of GDP):	(1) Official development assistance (ODA)	(2) Migrants' remittances	(3) Lending from multilateral institutions	(4) Bank and trade-related lending	(5) Foreign direct investment	(6) Portfolio investment
Coefficient on storm index:						
Year 0	0.058 (0.031)*	0.01 (0.014)	-0.004 (0.010)	0.009 (0.043)	-0.036 (0.032)	-0.029 (0.031)
Year -1	0.072 (0.036)*	0.005 (0.022)	0.021 (0.011)*	-0.02 (0.021)	-0.012 (0.024)	0.042 (0.043)
Year -2	0.08 (0.047)*	0.003 (0.012)	0.013 (0.007)*	-0.044 (0.037)	-0.026 (0.045)	-0.005 (0.034)
Year -3	0.069 (0.036)*	-0.024 (0.017)	0.028 (0.014)*	-0.018 (0.038)	-0.001 (0.049)	0 (0.026)
Year -4	0.057 (0.038)	-0.012 (0.018)	0.001 (0.012)	-0.005 (0.039)	0.015 (0.050)	0.046 (0.049)
Year -5	0.053 (0.030)*	-0.043 (0.021)**	0.022 (0.018)	-0.015 (0.039)	-0.013 (0.025)	-0.006 (0.024)
Year -6	0.086 (0.023)***	0.042 (0.036)	-0.006 (0.036)	0.028 (0.032)	-0.027 (0.020)	0.011 (0.021)
Year -7	0.038 (0.030)	0.028 (0.045)	-0.016 (0.016)	0.019 (0.031)	-0.02 (0.022)	0.06 (0.037)
Num. of obs.	1,098	737	1,002	1,002	894	921
R-squared	0.81	0.91	0.44	0.52	0.67	0.29
Sum of coefficients, years 0 to -3	0.28 (0.14)**	-0.01 (0.05)	0.06 (0.03)**	-0.07 (0.12)	-0.07 (0.14)	0.01 (0.06)
Sum of coefficients, years -4 to -7	0.23 (0.11)**	0.02 (0.11)	0 (0.05)	0.03 (0.11)	-0.04 (0.11)	0.11 (0.1)
Sum of coefficients, years 0 to -7	0.51 (0.25)**	0.01 (0.1)	0.06 (0.04)	-0.05 (0.23)	-0.12 (0.24)	0.12 (0.13)

* 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.

Appendix Table 5: Impact of storms on international financial flows to developing countries, 1970-2002
Countries below median initial per capita GDP
(Fixed effects OLS estimates)

Dependent variable (share of GDP):	(1) Official development assistance (ODA)	(2) Migrants' remittances	(3) Lending from multilateral institutions	(4) Bank and trade-related lending	(5) Foreign direct investment	(6) Portfolio investment
Coefficient on storm index:						
Year 0	0.169	0.088	-0.01	-0.127	-0.065	0.001
	(0.181)	(0.049)*	(0.077)	(0.088)	(0.053)	(0.013)
Year -1	-0.213	0.105	-0.138	-0.138	0.14	0.002
	(0.234)	(0.039)**	(0.053)**	(0.031)***	(0.059)**	(0.011)
Year -2	0.451	0.094	0.074	0.131	-0.056	0.014
	(0.306)	(0.039)**	(0.053)	(0.075)*	(0.064)	(0.021)
Year -3	0.313	0.06	0.093	-0.012	-0.02	-0.02
	(0.550)	(0.039)	(0.094)	(0.058)	(0.034)	(0.018)
Year -4	0.084	0.008	-0.048	0.057	0.027	0.011
	(0.147)	(0.034)	(0.032)	(0.052)	(0.046)	(0.009)
Year -5	-0.258	-0.001	-0.028	-0.046	-0.057	-0.047
	(0.103)**	(0.029)	(0.067)	(0.022)**	(0.052)	(0.051)
Year -6	-0.24	0.012	-0.049	0.022	0.016	-0.013
	(0.074)***	(0.043)	(0.033)	(0.027)	(0.063)	(0.024)
Year -7	-0.044	-0.055	0.076	0.01	-0.036	-0.014
	(0.091)	(0.067)	(0.031)**	(0.031)	(0.043)	(0.023)
Num. of obs.	1,014	684	1,011	1,011	737	730
R-squared	0.82	0.98	0.68	0.37	0.51	0.36
Sum of coefficients, years 0 to -3	0.72	0.35	0.02	-0.15	0	0
	(0.4)*	(0.12)***	(0.07)	(0.07)**	(0.09)	(0.03)
Sum of coefficients, years -4 to -7	-0.46	-0.04	-0.05	0.04	-0.05	-0.06
	(0.1)**	(0.14)	(0.07)	(0.09)	(0.12)	(0.09)
Sum of coefficients, years 0 to -7	0.26	0.31	-0.03	-0.1	-0.05	-0.07
	(0.48)	(0.23)	(0.11)	(0.13)	(0.17)	(0.11)

* 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.

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