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Foreign Aid in the Aftermath of Large Natural Disasters

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Abstract

This paper examines Official Development Assistance (ODA) in the aftermath of large natural disasters between 1970 and 2008. Using an event-study approach, the paper finds that while the median increase in ODA is 18% compared with pre-disaster flows, the typical surge is small in relation to the size of the affected economies. Moreover, aid surges typically cover only 3% of the total estimated economic damages caused by the disasters. The main determinants of post-disaster aid surges are found to be the intensity of the event itself and the recipient country's characteristics such as the level of development, country size and the stock of foreign reserves. The paper does not find evidence that political considerations or strategic behavior on the part of donors determine the size of post-disaster aid surges.

1. Introduction

Human and economic catastrophes associated with natural hazards are obviously not new, even if new media have changed the way we are aware of them. The January 2010 earthquake in Haiti and the Indian Ocean tsunami of 2004 both generated much international media attention and unprecedented amounts of international pledges of aid from private charities, non-governmental organizations (NGOs), governments and multilateral organizations.[1] Nonetheless, aid pledges made while media attention is at its peak may not always be disbursed, could take a long time to arrive, or may replace previously pledged aid. This raises the following questions: (1) How much does foreign aid really increase in the aftermath of large disasters? (2) Are aid surges sizable in relation to the estimated economic damages caused by disasters? (3) What determines the actual size of the surges?

As far as we could find, no one has ever looked at these questions systematically, in spite of their obvious importance. One stumbling block is that data sources that describe emergency international assistance (for example, the United Nations' Financial Tracking Service database), do not compare their information with disbursements prior to the event. Therefore, it may be that much of these resources recorded as post-disaster aid would have been provided anyway (i.e. without a disaster occurring).[2] We try to avoid this problem by exploiting the data available through the Organisation for Economic Co-operation and Development's (OECD's) Official Development Assistance (ODA) dataset which tracks bilateral aid flows from 44 donor countries (32 OECD and 12 non-OECD) to 165 recipient countries since 1960. Therefore, using an event study approach, we present estimates of the actual surges in aid flows that affected countries experienced following large natural disasters.

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Our results suggest a mixed picture: while ODA typically increases significantly relative to pre-disaster flows (i.e. median aid flows increase by 18% after disasters), post-disaster aid surges are usually small compared with the size of the economies (i.e. the median increase is 0.14% of GDP), and to the actual direct damages caused by the events (i.e. the median aid surge covers less than 3% of total estimated damages). From a normative standpoint, whether these amounts of aid are high or low for development purposes is debatable because such an assessment would require a study on aid effectiveness. Instead, the point that we make in this paper is that post-disaster aid surges are typically small in relation to the overall damages caused by the disasters.

After calculating the magnitudes of post-disaster aid surges, we extend the event study approach to examine the determinants of the size of these surges. Not surprisingly, we find that the severity of the event is a determinant of the post-disaster aid surge. In addition, we find richer countries—conceivably with more resources available to be re-directed toward reconstruction—receive less foreign aid in the aftermath of natural disasters. Similarly, countries with larger stocks of foreign exchange reserves—i.e. more resources available to use for importing capital goods to facilitate reconstruction—are also given less aid. We also find that media reporting of a disaster is positively related with larger aid inflows, although media attention is largely correlated to the severity of the event. In addition, we find that initial pre-disaster international humanitarian support reduces post-disaster aid inflow surges. Finally, we do not find evidence that supports the commonly held views that political/cultural affinity between donors and affected countries and geopolitical interests drive donor behavior following catastrophic natural events.

Based on these findings, we conclude that while some countries could expect to receive more aid than others, the evidence suggests that the expectation of large surges in post-disaster aid flows is not warranted given the current configuration of global foreign aid. Therefore, we conjecture that countries facing potentially big losses from natural disasters should not expect foreign aid inflows to cover a large proportion of the hefty toll that these events usually impose.[3] This stresses the need for vulnerable countries to develop complementary sources of financing for post-disaster relief in order to help to manage risks efficiently.

The structure of the paper is as follows. First, we review the related literature in order to place our contribution in context. Next, we discuss the data and introduce some stylized facts on post-disaster aid flows based on an event study approach. We then explore the determinants of aid surges using a cross-section of events. Finally, we conclude with discussion and topics for further research.

2. The Literature on Emergency International Assistance

Few papers examine post-natural disasters aid flows. Yang (2008) uses hurricane intensity data and concludes that official foreign aid increases significantly after disasters; for the developing countries in his sample, 73% of disaster damages are ultimately covered by aid inflows.[4] David (2011) examines a similar question but with a different empirical approach. He finds that aid does not seem to increase after climatic disasters, and their increase following geological ones is delayed and very small. This divergence in results suggests the need to revisit the question using a larger sample of countries and events and different methods.[5]

Strömberg (2007) is interested in answering two questions: whether the amount of aid given after a disaster is influenced by news coverage of the disaster (the answer:

yes); and whether a potential donor country is more likely to give aid if it has a well-established connection with the affected country (the answer is again: yes). Our approach is different methodologically, and our answers are correspondingly different.

Not surprisingly, the hypothesis that foreign aid is also affected by geo-strategic interests has also been examined empirically. A large number of papers focus on the politics of aid given by the USA (without focusing on post-disaster aid), and most emphasize that geo-strategic and political interests play a large role in determining US aid allocations across space and over time (recent examples are Drury et al., 2005 and Fleck and Kilby, 2010). However, others suggest a humanitarian motivation is also evident (e.g. Demirel-Pegg and Moskowitz, 2009).[6] While we do not focus on the determinants of aid allocation across space and time, in this paper we find no evidence that political factors are determinants of post-natural disasters aid surges.

Beyond these supply factors guiding aid allocations, Olsen et al. (2003) note that demand factors (i.e. the receiving country's characteristics), and in particular its readiness to absorb new flows through NGOs, are important in determining aid inflows. In contrast, they find little evidence that policy effectiveness by the receiving government and the presence of efficient institutional capacity to implement aid matter for the magnitude of aid donations (though this may vary by the nature of the donating source; see Easterly and Pfutze, 2008).

In work that is similar to ours in its approach even if the subject matter and specific empirical methodologies are different, Kang and Meernik (2004) examine the increase in aid following armed conflict.[7] They quantify the average post-conflict surge in aid and attempt to explain the size of the surge by the nature of the conflict and the regime type that reigned at its end.

Agénor and Aizenman (2010) examine aid surges and argue, with the support of a theoretical model, that aid volatility potentially leads to poverty traps. In spite of this adverse risk imposed by aid volatility, they find that under certain conditions self-insurance (i.e. a contingency fund) that would ameliorate this volatility is sub-optimal since its existence distorts donors' motivations. Some supporting evidence regarding this "moral hazard" problem is provided by our findings on the availability of domestic resources (in particular foreign reserves) as an important determinant of post-disaster aid allocations.[8]

These papers suggest different hypotheses that are worthwhile examining within the context of post-disaster aid allocations. Our contribution is to emphasize a different (and we think more accurate) measure of post-disaster aid that we calculate based on the baseline aid flows that precede the disaster. Using this novel measure of post-disaster aid-surges, we are able to shed light both on the determinants of these aid flow surges and examine several hypotheses concerning these determinants.

3. Data

Disaster and Aid Data

Almost all the empirical work on natural disasters relies on the publicly available Emergency Events Database (EM-DAT) maintained by the Center for Research on the Epidemiology of Disasters (CRED) at the Catholic University of Louvain, Belgium (http://www.emdat.be/). EM-DAT defines a disaster as a natural situation or event which overwhelms local capacity and/or necessitates a request for external assistance. For a disaster to be entered into the EM-DAT database, at least one of the following criteria must be met: (i) 10 or more people are reported killed; (ii) 100 people are reported affected; (iii) a state of emergency is declared; or (iv) a call for international assistance is issued. Disasters can be hydro-meteorological, including floods, wave surges, storms, droughts, landslides and avalanches; geophysical, including earthquakes, tsunamis and volcanic eruptions; and biological, covering epidemics and insect infestations (the latter are less frequent).

The disaster impact data reported in the EM-DAT database consists of direct damages (e.g. value of damage to infrastructure, crops, and housing in current dollars), the number of people killed and the number of people affected.[9] As Cavallo and Noy (2011) observe, many of the events reported in this database are quite small and are unlikely to have any significant impact on aid disbursements and on the macro-economy more generally. We therefore limit our investigation to disasters in which the number of people killed is above the mean for the entire dataset (more on this below).[10]

Detailed data on aid flows are available from the OECD's Development Assistance Committee (OECD-DAC) and from the United Nations' Financial Tracking Service (UN-FTS). The OECD-DAC data on official development assistance cover annual bilateral aid extended from 44 donor countries (32 OECD and 12 non-OECD plus several multilateral agencies) to a large number of recipient countries. The UN-FTS database does not aggregate aid flows annually but rather presents information for each international humanitarian aid appeal issued by the UN. Many of these appeals involve natural disasters.

The UN-FTS data have two advantages: First, they provide data for each appeal separately, hence allowing direct one-to-one correspondence between aid flows and individual disasters. Second, while the OECD-DAC focuses only on OECD donor governments and multilateral organizations, the UN-FTS also tracks aid flows of some large private/NGO donors. However, UN-FTS data are based on donors' voluntary reporting and may significantly mis-estimate the volume of actual new aid given.

We choose to use the OECD-DAC data because of its more comprehensive nature and because it is based on actual disbursements rather than pledges or commitments. Thus, we can directly estimate by how much foreign official aid increases in the aftermath of disasters instead of focusing on undisbursed pledges or on re-labeled flows. Moreover, while the OECD-DAC data do not separately measure post-disaster aid, the event study methodology we apply seeks to overcome this problem. By comparing aid flows before and after a natural disaster, we are able to calculate the actual aid surge observed from aid data; we assume this aid surge is related only to the disaster itself.[11]

For further disaster data for the period 1970–2008 see Table S1 in the Supporting Information (for access details see the end of the paper).

Descriptive Statistics on Aid and Disasters

There are a total of 6,530 events recorded in the EM-DAT database between January 1970 and June 2008, of which 3,097 (47.4%) are floods, 2,617 (40.1%) are storms and 816 (12.5%) are earthquakes. Oftentimes there are multiple events recorded in a given country–year. In those cases, we add up the corresponding disaster magnitudes and define a "combined" disaster for that country–year observation.[12]

Disasters are fairly common. Out of a total of 7,644 year–country observations (196 countries × 39 years), 1,658 (22%) meet the requirements to be designated as a natural disaster. However, as already noted, large events are less common. When we restrict the sample only to large events and where "large" is defined to be larger than the world mean of 31 people killed per million inhabitants, only 137 year–country observations remain. We further exclude 17 additional observations either because they coincided with another major event in the country that also could have affected foreign aid (e.g. Afghanistan in 2002) or we found some anomalies in the aid data.[13] Out of the remaining subset of events, 98 have the full set of information required to do the event study we pursue here (particularly aid data in the OECD-DAC dataset). This is the sample of events that we study.

In other words, an "event" in our sample is a country–year observation for which: (i) there is record in the EM-DAT database of one or several natural disasters that hit the country in that year that caused at least as many fatalities as the world mean for the entire time period; (ii) the disaster itself was not too small in absolute terms; (iii) aid data are available to perform the event study analysis; and (iv) the observation is not an obvious outlier, nor does it or coincide with another major event that could have triggered an aid surge.[14]

In order to evaluate the robustness of the results to small variations in the sample of events, we disaggregate events into three sub-samples. Sample 1 includes all of the disasters described above. Sample 2 excludes the events that overlapped with other natural disasters in the same country within a two-year window. Sample 3 includes overlapping events but excludes observations in which there were multiple disasters in a given year and for which intensity data (i.e. number of killed people or economic damages data) were not available for at least one of these events. Sample 1, the most comprehensive, includes 98 events, while the most restrictive sample, Sample 2, includes only 68 disasters.

Table 1 presents summary statistics and the first set of results for the event study. An "aid surge" is computed as the difference between the average aid flows up to two years after the disasters and the average aid flows in the two years preceding disasters.[15] We also calculate the medians of the severity of the disasters (in terms of number of people killed and direct economic damages).[16]

In the case of sample 1, the median mortality per disaster was 474 people, or 80 people killed per million inhabitants. The median economic damage was 5.7% of GDP. In terms of the "aid surge" post disaster, we find that median post-disaster aid increased by approximately 18% compared with the pre-disaster average flows. This is equivalent to 0.25% of recipient countries' GDP. The numbers for the other samples are very similar, suggesting that the results are not driven by a particular subset of events.

In order to get a better understanding of the dynamics of post-disaster foreign aid flows, Figure 1 presents the data on aid flows in the years before and after the disasters. The figures are standardized so that the average of pre-disaster aid inflows is equal to 1. When examining the averages, aid flows already appear to increase in the year of the disaster (by 8% for Sample 1) and then increase further in the year after the disaster by about 20%. Aid flows dip somewhat in the second year after the disaster, depending on the sample, but they do not revert to their pre-disaster levels in the six years we track following the disaster.

Taken together, these results suggest that official foreign aid increases in the aftermath of large natural disasters and does not revert to pre-disaster trends for at least six years after the event. However, the size of these surges is typically

Table 1. Descriptive Statistics for Post-disaster Surges

Sample	*Observations*	*Number of people killed*	*Killed per million of inhabitants*	*Economic damages (2000 US$ millions)*	*Economic damages (% of GDP)*	*Aid surge (2000 US$ millions)*	*Aid surge (% of GDP)*	*Coverage ratio (% of damages)*	*Aid surge (%)*
Sample 1	98	474	80.1	350.1	5.7	11.5	0.251	2.9	17.8
Sample 2	68	486	74.1	417.5	4.2	14.2	0.222	3.2	18.7
Sample 3	92	443	81.0	350.1	5.7	12.2	0.292	3.4	18.1

Note: Event window: 2 years.
Source: Authors' calculations based on EM-DAT and WDI datasets.

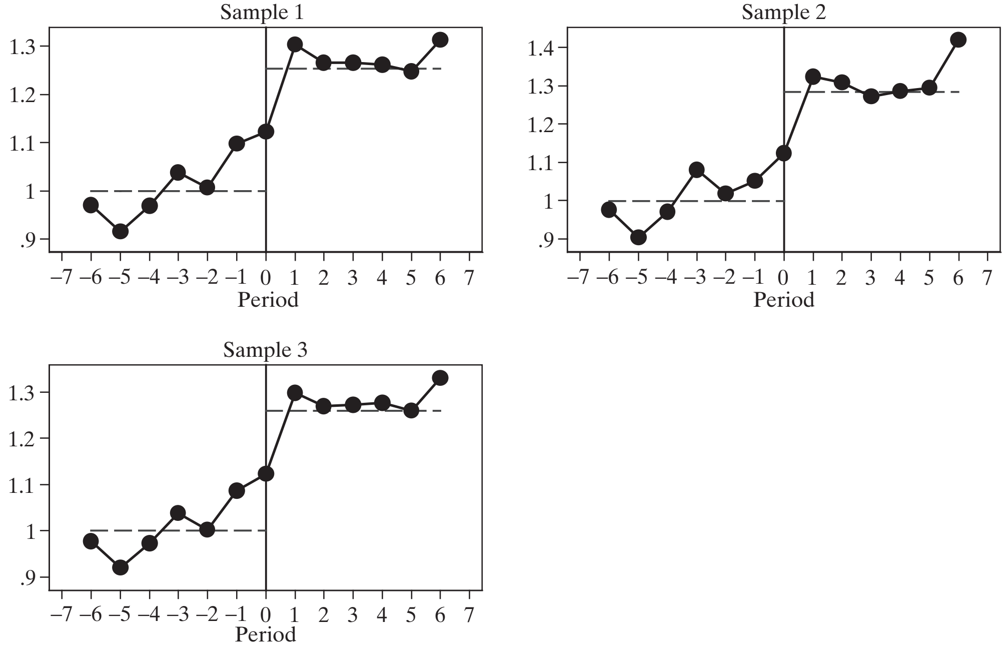

Figure 1. Before–After Aid Flows

small *vis-à-vis* the estimates of the direct economic damages caused by the disasters.

4. Determinants of Post-disaster Aid Surges

Having defined and quantified aid surges for a cross-section of events, we exploit the variability in the data to try to explain the determinants of the size of these surges. In other words, we extend the event study approach presented in the previous section to explore the empirical determinants of post-disaster aid surges. In order to do so, we pool together the 98 events described in the previous section and conduct a multivariate regression analysis.

The selection of explanatory variables included in the regressions is guided by insights from the literature of the determinants of foreign aid. In particular, besides obvious determinants of post-disaster aid surges like the severity of the events, we assess whether post-disaster aid surges are also politically and/or strategically motivated. We also test whether other resources available to the country influence donors' actions.

In regard to methodology, we employ an event study approach that is designed to estimate the determinants of post-disaster aid surges. We do not follow the standard panel data approach used in the literature on the determinants of foreign aid because we do not wish to estimate the determinants of foreign aid flows across space and time. Instead, we are interested in examining the determinants of the aid surges that can be convincingly attributed to the occurrence of a large adverse shock (disaster).[17]

Model Specification

We estimate regressions of the following type:

$$\begin{aligned}\Delta \ln Aid_{i,t} = {} & \beta_0 + \beta_1 \ln Aid_{i,t-1} + \beta_2 \ln Intensity_{i,t} + \beta_3 \ln(1 + Media\ Coverage)_{i,t} \\ & + \beta_4 \ln(GDP/Pop)_{i,t-1} + \beta_5 \ln GDP_{i,t-1} \\ & + \beta_6 \ln(Reserves/GDP)_{i,t-1} + \beta_7 Affinity_{i,t-1} + u_{i,t}\end{aligned}$$

The dependent variable is the same as in the previous section. It is computed as the log difference between average post-disaster aid flows (up to two years after the disaster, including the disaster year itself) and average aid flows in the two years preceding the disaster. The subscript i denotes the event location, and the subscript t denotes the year of the event. As a result, every pair i, t denotes one of the 98 events in Sample 1 described in the previous section.

When deciding on control variables, we rely on benchmark specifications on the determinants of aid, as used most recently in Werker et al. (2009) and Fink and Redaelli (2009). Details on the variables and their sources are shown in Table 2.

Our list of control variables includes the following:

- $\ln Aid_{i,t-1}$: The natural logarithm of the initial pre-disaster aid level (average aid flows of two years preceding the event). We include this variable to assess the impact of pre-disaster aid relationships on post-disaster aid allocation.
- $\ln Intensity_{i,t}$: Either the natural logarithm of the reported amount of economic damages caused by the disaster(s), or the number of people killed in the immediate aftermath of the event(s). This is included to assess how the catastrophic nature of the events shapes the post-disaster aid response.
- $\ln(1+Media\ Coverage)_{i,t}$: The natural logarithm of 1 plus media coverage of the disaster measured by the number of stories about it published in the Associated Press within a six-month period following the event. Media attention helps to raise awareness about the destructive nature of the events and, as a result, it may influence the post-disaster aid response.
- $\ln(GDP/Pop)_{i,t-1}$: The natural logarithm of the country's pre-disaster GDP per capita. The inclusion of this variable allows us to assess whether the level of economic development is a determinant of post-disaster aid allocation.
- $\ln GDP_{i,t-1}$: The natural logarithm of pre-disaster real GDP (US$ 2000). We use it as a proxy for country size. The aid literature has long observed that small countries tend to receive a larger per capita share of aid.
- $\ln(Reserves/GDP)_{i,t-1}$: The natural logarithm of pre-disaster foreign exchange reserves (as a percentage of GDP). We include this variable to take into account that the availability of alternative funding may influence the size of the post-disaster aid surge.
- $Affinity_{i,t-1}$: Political affinity index (based on the UN voting patterns). We include this variable to test if post-disaster aid allocation is influenced by political considerations like the political affinity between recipient and donor countries. Geopolitical considerations are frequently mentioned in the literature on donor motivations in providing aid.

Regression Results

The estimation results for the determinants of aid surges are presented in Table 3. Each column represents a different regression specification. The effective sample size in each case is determined by data availability for the control variables.[18]

Table 2. Data Sources

Variable	*Source*	*Notes*
ODA total net disbursements	OECD DAC Database. Available at http://stats.oecd.org/	US$ 2000m
Economic damage	EM-DAT Database. Available at http://www.emdat.be/database	US$ 2000m
Number of people killed	EM-DAT Database. Available at http://www.emdat.be/database	Total
Media coverage	Associated Press Archive. Available at http://www.aparchive.com/	Number of reports
Real GDP	World Development Indicators Database. Available at http://data.worldbank.org/data-catalog/world-development-indicators	US$ 2000 dollars
Population	World Development Indicators Database. Available at http://data.worldbank.org/data-catalog/world-development-indicators	Total
International reserves over GDP	World Development Indicators Database. Available at http://data.worldbank.org/data-catalog/world-development-indicators	Ratio
Political affinity index	The Affinity Of Nations Index database (Version 4.0). Available at http://dss.ucsd.edu/~egartzke/htmlpages/data.html	Average with DAC countries, –1 (low affinity) to 1 (high affinity)
Land area	World Development Indicators Database. Available at http://data.worldbank.org/data-catalog/world-development-indicators	Squared kilometers
Openness to international trade	World Development Indicators Database. Available at http://data.worldbank.org/data-catalog/world-development-indicators	%. Author's calculations.
Armed conflict dummy	UCDP PRIO Armed Conflict Dataset. Available at http://www.prio.no/CSCW/Datasets/	Author's calculations
Small island state dummy	United Nations. Available at http://www.un.org/special-rep/ohrlls/sid/list.htm	
Former colony dummy	Correlates of War. Available at http://www.correlatesofwar.org/	Author's calculations
Type of disaster dummy	EM-DAT Database. Available at http://www.emdat.be/database	Author's calculations
Sovereign debt as percentage of GDP	Ugo Panizza debt dataset. Avaiable at http://sites.google.com/site/md4stata/linked/public-debt	Author's calculations
Polity IV's revised combined polity score	Polity IV project. Available at http://www.systemicpeace.org/inscr/inscr.htm	–10 (autocracy) to 10 (democracy)
ICRG corruption index	International Country Risk Guide dataset. Available at http://www.prsgroup.com/ICRG.aspx	0 (high corruption) to 6 (low corruption)
ICRG law and order index	International Country Risk Guide dataset. Available at http://www.prsgroup.com/ICRG.aspx	0 (low law and order) to 6 (high law and order)
Central government balance as percentage of GDP	World Economic Outlook dataset.	%

Table 3. Regression Results, Sample 1

Explanatory variables	*(2.1)*	*(2.2)*	*(2.3)*	*(2.4)*	*(2.5)*
Number of people killed	0.0681			0.0522	
(Total, logs)	[3.59]***			[2.50]**	
Economic damage		0.0345			0.0301
(US$ 2000m, in logs)		[1.70]*			[1.26]
Media coverage			0.0488	0.0319	0.0398
(1 + number of reports in AP archive, in logs)			[3.09]***	[1.86]*	[1.82]*
Initial Aid level	–0.144	–0.121	–0.167	–0.162	–0.161
(US$ 2000m, average previous to event, in logs)	[–3.79]***	[–1.76]*	[–3.76]***	[–3.93]***	[–2.45]**
Real GDP per capita	–0.0844	–0.151	–0.171	–0.12	–0.192
(US$ 2000m, average previous to event, in logs)	[–2.12]**	[–1.96]*	[–3.86]***	[–2.69]***	[–2.57]**
Real GDP	0.0282	0.0668	0.0786	0.0335	0.0673
(US$ 2000m, average previous to event, in logs)	[0.99]	[1.77]*	[3.14]***	[1.12]	[1.80]*
International reserves over GDP	–0.0721	–0.0678	–0.0911	–0.0861	–0.0951
(average previous to event, in logs)	[–2.25]**	[–1.56]	[–2.86]***	[–2.78]***	[–2.17]**
Political affinity index	0.16	0.369	0.26	0.193	0.339
(average previous to event, –1 to 1)	[0.54]	[0.83]	[0.78]	[0.63]	[0.77]
Constant	–0.252	–1.016	–0.836	–0.4	–1.095
	[–0.67]	[–1.99]*	[–2.29]**	[–1.04]	[–2.03]**
Observations	75	60	74	74	59
R^2	0.357	0.274	0.321	0.37	0.317
F-statistic (p-value)	0.00000	0.00267	0.00000	0.00000	0.00015

Notes: Dependent variable: Aid Surge (logs). Event window: 2 years. t-statistics in brackets computed using robust standard errors. *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

The R^2 for the different specifications vary between 0.27 and 0.37. While the explanatory power of our model is modest, this is in line with previous attempts to estimate the determinants of aid flows (e.g. Strömberg, 2007). However, reassuringly, the F-statistic for the joint significance of the explanatory variables is consistently statistically significant across the different specifications.

In column 1, we report the results of the benchmark specification. The results suggest that the severity of the event matters for post-disaster aid allocation. In particular, we find that a 10% increase in the severity of the disaster (measured in terms of the number of people killed) implies a 0.7% average increase in aid, conditional on the other control variables. The same qualitative result holds when the magnitude of the disaster is measured in terms of the size of economic damages (i.e. destroyed infrastructure and other direct costs, see column 2). In column 3 we examine whether media exposure is also a determinant of the supply of aid. While media coverage does indeed seem to increase the amount of post-disaster aid, a close examination (see columns 4 and 5) reveals that this effect is largely due to the correlation between the severity of the disasters (measured by either economic damages or fatalities) and media exposure. Over the entire sample, the correlation between number of people killed in the events and media coverage (in logs) is 0.61, whereas the same figure for media coverage and economic damages is 0.56. The result is intuitive: the most severe events capture more media attention. This in turn raises public awareness about the disaster and results in more post-disaster foreign aid.

One of the most robust results in the regressions is that a higher initial (pre-disaster) aid level is associated to lower aid surges. This result is consistent with the view that aid flows follow a persistent process, provided that aid is committed to projects with a long-run horizon.[19] An alternative non-competing interpretation for the negative estimated coefficient on initial aid is that there could be aid reallocation in the aftermath of natural disasters. This interpretation would be consistent with evidence presented by Benson and Clay (2004) who, using case studies, find that the aggregate post-disaster aid flows do not increase considerably because of re-allocation of pre-disaster aid flows.

In terms of the other control variables we find that, on average, countries with a higher real GDP per capita receive less post-disaster aid, controlling for the magnitude of the disaster. The same, however, is not true for the size in the economy: the larger the size of the economy, the bigger the aid surge a country will receive.

The amount of foreign exchange reserves that a country possesses also seem to matter for the size of the post-disaster aid flow. In particular, countries with more reserves receive less in international assistance. Therefore, this is evidence consistent with the view that donors' behavior may be influenced by their perception of the recipients' economic needs. This notwithstanding, given that the size of aid surges are small in relation to the damages caused by disasters, and given that the estimated crowding out is less than 1-to-1, then reserves accumulation and foreign aid should be viewed as complementary. In other words, foreign aid does not appear to be a substitute for other forms of country insurance against the consequences of natural disasters such as reserves accumulation.

Finally, the measure of political affinity is never significant in the estimations. While it is possible that this reflects a difficulty in measuring political interest when aggregating over several donor groups, the bottom line is that we do not find evidence supporting the hypothesis that post-disaster aid surges are driven by political motivations.

Robustness

The literature has suggested several other possible determinants of foreign aid. In unreported specifications we included the following additional control variables: (i) land area (square kilometers, in logs) as another proxy for country size; (ii) openness to international trade (total imports as percent of world total exports, in logs) since donor countries may possibly be more likely to assist trading partners in times of need; (iii) a dummy variable indicating whether or not there is an armed conflict in the country inhibiting aid flows following the time of the disaster; (iv) a dummy variable for small island states since these generally receive proportionally more aid; (v) a dummy variable for former colony status, as the former colonial master may be more likely to assist; and (vi) dummy variables for the type of disaster. In all cases, these coefficients were not significantly different from zero, suggesting either mismeasurement/misspecification or a lack of real correlation/causality. Importantly, however, the inclusion of these additional control variables did not change the results reported in the previous section.[20]

Finally, we also run panel regressions akin to those in the literature on the determinants of foreign aid. In order to do so, instead of pooling by events, we keep the country/year format of the original dataset, and we change the dependent variable to the actual aid flows by recipient country in every year (i.e. $Aid_{i,t}$). In terms of the explanatory variables, the main change is that the disaster intensity variables (i.e. economic damages or fatalities) and the proxy for media coverage were set to zero for those country/year observations in which there were no events. In other words, the model that we run is the following:

$$\ln Aid_{i,t} = \beta_0 + \beta_1 \ln Aid_{i,t-1} + \theta X_{i,t-1} + u_{i,t}$$

where θ and $X_{i,t-1}$ are a parameter vector and a vector including the remaining explanatory variables, respectively.

Given the characteristics of the panel and the fact that we included the lagged dependent variable in the regressions, we estimated the model by dynamic panel methods. The regression results, reported in Table 4, confirm the findings of the event study approach. In particular, based on the set of control variables included in the regressions, we find that the disaster intensity variables and the lagged dependent variable, are the main determinants of aid allocation.[21]

Notwithstanding the consistency of the results with our baseline estimation, we do not emphasize them because we think that the event study approach is better suited to address the question of the paper. In other words, a full assessment of the determinants of aid flows across space and time (which is essentially what the panel data approach does) is outside the scope of this paper.

In summary, the results of a battery of sensitivity tests confirm that the main determinants of foreign aid in the aftermath of natural disasters are: the intensity of the event itself, the pre-disaster level of aid, and the recipient country's characteristics such as the level of development, country size and the stock of foreign reserves available. Moreover, we do not find evidence that political considerations or strategic behavior on the part of donors determine the size of post-disaster aid surges.

5. Conclusion and Future Research

We estimated the size of post-disaster aid surges. Our results indicate that the median increase in realized post-disaster aid is approximately 18% compared with

Table 4. Regression Results, Data Panel Estimation

	Two step, system GMM estimation				
Explanatory variables	*(5.1)*	*(5.2)*	*(5.3)*	*(5.4)*	*(5.5)*
Number of people killed	0.0249			–0.00471	
(first lag, total, in logs)	[2.06]**			[–0.29]	
Economic damage		0.0335			0.00149
(first lag, US$ 2000m, in logs)		[2.48]**			[0.08]
Media coverage			0.0839	0.0948	0.0854
(first lag, 1 + number of reports in AP archive, in logs)			[3.36]***	[2.97]***	[2.55]**
Aid flows	0.538	0.538	0.537	0.536	0.534
(first lag, US$ 2000m, in logs)	[11.57]***	[11.47]***	[11.54]***	[11.43]***	[11.78]***
Real GDP per capita	–0.389	–0.391	–0.388	–0.39	–0.395
(first lag, US$ 2000m, in logs)	[–7.04]***	[–7.10]***	[–7.00]***	[–6.97]***	[–7.44]***
Real GDP	0.209	0.212	0.208	0.21	0.212
(first lag, US$ 2000 m, in logs)	[8.06]***	[8.01]***	[8.09]***	[7.92]***	[8.35]***
International reserves over GDP	–0.0185	–0.0188	–0.0186	–0.0178	–0.0205
(first lag, in logs)	[–0.93]	[–0.96]	[–0.91]	[–0.86]	[–1.01]
Political affinity index	0.0453	0.0679	0.0539	0.0527	0.0759
(first lag, –1 to 1)	[0.37]	[0.57]	[0.45]	[0.44]	[0.66]
Constant	–1.96	–2.023	–1.952	–1.976	–2.041
	[–4.69]***	[–4.84]***	[–4.67]***	[–4.63]***	[–5.09]***
Observations	3571	3555	3570	3570	3554
Number of countries	120	120	120	120	120
Number of instruments	120	120	120	121	121
Arellano–Bond AR(1) test (p-value)	5.33E-09	5.85E-09	6.1E-09	6.87E-09	5.82E-09
Arellano–Bond AR(2) test (p-value)	0.125	0.228	0.144	0.146	0.255
Hansen's Overidentification test (p-value)	0.302	0.291	0.304	0.304	0.308

Notes: Dependent variable: log of Aid Flows. In all regressions, time fixed effects are included (not shown). t-statistics computed using robust standard errors in brackets.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

pre-disaster flows. While this is potentially a significant amount, the median aid surge covers only a small fraction of estimated direct damages caused by the disasters. This suggests that vulnerable countries need to plan for complementary sources of financing during the recovery phase.

In terms of the determinants of the size of post-disaster aid surges, we find that damages caused by the disaster are positively related to subsequent aid inflows, but that higher incomes and higher incomes per capita, *ceteris paribus*, are associated with lower post-disaster aid flows. More foreign exchange reserves are also associated with less post-disaster aid being provided. We do not, however, find evidence that post-disaster aid inflows are positively associated with measures of political affinity and geo-strategic interests of donor countries.

We view this paper as the "opening shot" in a larger research effort to understand post-disaster reconstruction. In this paper we have not addressed important issues like, for example, the effectiveness of post-disaster aid allocation in mitigating the consequences of disasters, or the optimal composition of foreign aid for development purposes.

A different set of questions, and one that has not really been tackled in any comparative way, focuses on identifying the most productive ways in which post-disaster aid should be disbursed (quickly as a lump-sum or sequenced over time?, in-kind or in-cash?). Observers have pointed out that large aid surges lead to higher prices and may therefore be less effective. Is this indeed the case? Should aid nevertheless concentrate on reconstructing as quickly as possible, in spite of the higher costs? What about the trade-off between quickly rebuilding what was there before and a slower rebuilding process that also accounts for newly exposed hazards and vulnerabilities and attempts to develop more resilient communities? We expect to see more research along these themes in the near future.

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Notes

1. For example, according to the UN, total disbursements for relief in the countries affected by the Indian Ocean tsunami reached US$1.25bn and US$3.59bn was disbursed for relief in Haiti through official channels or large donors (http://fts.unocha.org/, accessed 25 May 2012).
2. Poor countries, the usual recipients of foreign aid, are disproportionally affected by natural disasters (see Cavallo and Noy, 2011).
3. This would be especially true for catastrophic disasters (i.e. those that fall significantly outside the normal distribution of disaster damages). See the general discussion in Noy (2013) and the estimates for the Haiti 2010 earthquake damages vs its aid inflows (Cavallo et al., 2010).
4. Yang's sample is concentrated in a few island nations, the countries of Central America and two big countries that frequently experience storm damage, Bangladesh and the Philippines.
5. Both papers attempt to estimate the impact of disasters on financial flows more generally.
6. Raschky and Schwindt (2012), using data on specific post-disaster bilateral donations, analyze a different political-economy aspect. They focus on the reasons for donors' choices whether to channel the aid through a multilateral and whether to provide aid as cash or in-kind.
7. They examine the determinants of these aid surges using an 11-year cross-country panel with a conflict binary variable.
8. Raschky and Schwindt (2011) focus on a different aspect of this "moral hazard" which they term the "Samaritan's Dilemma".
9. The measure for direct damages does not include indirect impacts caused by the damage to physical infrastructure and productive capacity. Indirect damages can also be a consequence of the fact that reconstruction pulls resources away from normal production.
10. The two other papers that are closest to ours in their interest use more lenient criteria for inclusion. Fink and Redaelli (2009) use a sample of 400 disasters in the last 15 years, while Raschky and Schwindt (2012) use 228 disasters from 2000 to 2007.
11. It is possible that another event that had an impact on aid flows happened concurrently. However, since the specific timing of large natural disasters is largely unpredictable it seems reasonable to assume that our event study approach overcomes this problem in a large enough sample.
12. To avoid over-representation of small countries, before the country-year aggregation we exclude 1,436 very small events, defined as those with fewer than 10 people reported dead or missing and for which reported damages are less than US$10m.

13. Dropped events are: Afghanistan (2002), war in Afghanistan; Bangladesh (1973), post-Independence process; Haiti (1994), UN political intervention after the 1991 *coup d'état*; Iran (1972), several military conflicts, aid flows dropped by almost 70%; Saint Lucia (1980), Saint Lucia's independence from the UK; Turkey (1999), historically low levels of aid (post-disaster aid flows increased by almost 500%); and Venezuela (1999), historically low levels of aid in 1997 (aid after disaster increased by almost 200%). In five cases, the annual variation of the aid flows exceeds 300%. Five additional events were identified as outliers in the estimation procedure.
14. A list of these events is available in an Appendix Table included in the Inter-American Development Bank working paper version of our paper.
15. Excluding the year of the disaster itself from the post-event averages does not change the results.
16. We prefer to focus on the medians here because averages may be skewed by a few big outliers.
17. In order to verify the robustness of our results, however, we do estimate the determinants within a more common panel-dataset framework. See the next section for details.
18. Regression results based on samples 2 and 3 yield similar results and are available from the authors upon request. Given that the regression results are very similar, we only discuss the results for regressions based on Sample 1 which is the most comprehensive sub-sample.
19. To see this, notice that our benchmark equation can be rewritten as

$$\ln Aid_{i,t} - \ln Aid_{i,t-1} = \beta_0 + (\alpha - 1)\ln Aid_{i,t-1} + \theta X_{i,t-1} + u_{i,t}$$

where α is the autoregressive coefficient of the process, and θ and $X_{i,t-1}$ are vectors of parameters and explanatory variables, respectively. We consistently find that $\alpha - 1 < 1$, which suggests that the process is auto-regressive and aid flows are persistent.
20. Several other variables were not included since they reduced the sample significantly. These were: sovereign debt as percentage of GDP, Polity IV's revised combined polity score measuring the political regime on an autocratic–democratic scale range, the International Country Risk Guide (ICRG) corruption index, the ICRG law and order index and central government balance as percentage of GDP.
21. Note that, given the different model specification *vis-à-vis* the case study approach, the positive coefficient on the lagged dependent variable in the case of the panel data model is consistent with the negative coefficient in the pre-disaster aid flows in the case of the event study. In both cases, higher initial aid (Aid_{t-1}) results in larger post-disaster aid (Aid_t in the panel data setting) which is equivalent to lower aid surge (ΔAid in the case study setting).

Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's web site:

Table S1. Disaster Data