Supplementary Information for

Humanitarian Need Drives Multilateral Disaster Aid

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This PDF file includes a detailed description of how we conducted the meteorological re-analysis, collected the social data and developed the metrics, followed by a detailed overview of robustness checks.

SI Text

Tables S1 to S21

Figure S1

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Validation of disaster data and calculation of hazard severity

In the investigation of factors determining the distribution of United Nations (UN) disaster aid, the frequency of occurrence and degree of extremity of meteorological events are used to represent physical *hazard severity*. For deriving a hazard severity measure which captures meteorological extremes, a global-scale, temporally complete set of meteorological data is needed. While meteorological observations taken at fixed measurement sites capture point magnitudes with high accuracy, they are few and far apart. In-situ observations are also not easily utilized due to operational inconsistencies and uneven geographic density of measurement stations (1, 2), leading to difficulties in developing a reliable global data set spanning all countries. Another type of historical data, meteorological reanalysis, allows estimates of past atmospheric conditions by assimilating and combining observational data with forecasting models to reconstruct spatially and temporally coherent records. There are limits to the abilities of reanalysis methods in reproducing the absolute magnitude of local extremes in meteorological variables, primarily due to model resolution – it is not feasible to model at spatial scales small enough to resolve such processes as convection leading to convective storms or cloudbursts (3, 4), variations in terrain on the sub-grid scale leading to deviations of wind speeds from the grid cell mean (5), and impacts of the urban landscape on surface temperature extremes (6). Despite these limitations, using a reanalysis data set provides a coherent data set with the required global coverage and daily resolution.

We use the European Center for Medium-range Weather Forecast's ERA-Interim reanalysis data (7), based on the IFS Cy31r2 forecast model, to test the types of disasters most likely to be closely linked to controlling meteorological factors: flooding (high daily and 30-day accumulated precipitation), cold waves (low daily minimum temperatures at 2 m above surface), heat waves (high daily maximum temperatures at 2 m above surface), storms (high daily maximum sustained wind speeds at 10 m above surface), and drought (low 90- and 180-day accumulated precipitation). A spatial grid resolution of 0.75°x0.75° (at the equator: 83.5 km in the east-west direction, 82.9 km in the north-south direction) is used. Precipitation values are derived from daily sums of total precipitation and summation on different time scales. Maxima and minima in temperature and wind speed are taken from 3-hourly time steps. Temperature maxima and minima derived from retrieving 3-hourly time steps has been shown to better represent observations than those retrieved from 12-hourly time steps (8). Here, the same method has been applied in determining daily maximum wind speed at 10 m (the ERA-Interim daily variable most suited to represent near-surface wind values).

The analysis of meteorological severity presented in this study is carried out using comparisons of distributions of values and their frequency of occurrence, rather than using the absolute magnitudes of local extremes in terms of physical quantities, as the latter may not be accurately represented in the given record. They may be lost to area averaging, or the physical processes leading to them may not be resolved at the scale of the grid cell. Therefore, we must instead assume that the extreme meteorological events on smaller scales are driven, or represented by anomalous circumstances on a larger scale. Extremes are thus here defined and interpreted in the context of a parameter value's place in the overall distribution of values of that parameter, from the same atmospheric reanalysis, and are thus standardized and comparable.

This approach is common in detecting and measuring droughts using the standardized precipitation index (SPI), which is defined as the accumulated precipitation's number of standard deviations from the climatological mean (9). Using differing time scales allows a number of conditions to be examined: shorter time scales can impact soil moisture and thus agriculture, but not reservoirs or groundwater, leaving urban areas relatively unaffected (10). High accumulated precipitation in the short- to medium-term time scale may also cause high stream flow and increased flooding conditions. For these reasons, different time scales are compared for floods (daily and 30-day) and droughts (90-day and 180-day) in order to determine which time scales are more representative of extreme conditions in ERA-Interim. For droughts, the use of 3-month (here 90 days) accumulated precipitation accounts for seasonal variation (11), but a longer 6-month (here 180 days) accumulation time scale is also compared here to account for variation between years. For both floods and droughts, however, circumstances leading to the disaster may include other factors (both meteorological and not) such as soil moisture and humidity, which other, more complex indices take into account (12).

Similarly, the upper percentile values of overall daily maximum wind speed distributions have been used as a measure of storminess, which can refer to both frequency and intensity of storms, capable of causing a damaging impact upon society, for the purpose of insurance models and projections for hazards in future climates (13, 14). As wind gust fields are parameterized in models and are highly dependent upon topography, the use of wind gusts present problems with high variation within the scale of a single grid cell and thus sustained wind speed are preferred here, the use of which may lead to an underestimation in the true extremity of wind conditions during storms as instantaneous gusts are the likely meteorological condition to cause damage (15).

Comparisons of model extremes and climatological distributions of meteorological variables to observations is of keen interest in ongoing research. In recent years, it has led to the emergence of a field within meteorology known as *attribution analysis*, referring to the process of quantifying the contributions of factors such as anthropogenic global warming to an extreme event by investigating the circumstances leading up to the event and the range of physical conditions that lead to its occurrence (16). The ongoing research in attribution of weather progresses understanding of the performance of models (both global climate models and forecast models such as those used for reanalysis) in reproducing extreme events and their frequency, as well as methods of defining and detecting meteorological extremes. Similar to statistical methods used in attribution studies (17), here we use distributions of reanalysis data in order to describe extreme circumstances in comparison to a reference state as a measure of hazard severity.

Step 1: Validation of EM-DAT disaster data

In order to assess the ability of the reanalysis data to capture extreme meteorological events that coincide with reported disasters, the reanalysis data set is first checked against disasters reported in the Emergency Events Database (EM-DAT) (18). In order to identify the location of these disasters, we rely on a geocoded extension of the EM-DAT (23). From this dataset we obtain geographic information on the first-order administrative units within a country that were reported to be affected by the different disasters from EM-DAT. A variety of variables are used to detect signals of ERA-Interim statistical extremes that coincide with EM-DAT-listed disasters. Statistical extremes refer to a shift in the distribution of the meteorological variable during reported disasters, away from the climatological distribution in the reanalysis, representing abnormally high or low values in the given variable.

To test ERA-Interim values during EM-DAT-reported extreme conditions against all-time values, we use EM-DAT-reported disasters of the aforementioned types during the period 2006-2018, including only those events that also contain information of the administrative regions and dates of the disasters. We extract the corresponding ERA-Interim data, and the distributions of these extracted values are compared to the overall distributions of the variable during the same time period to detect a shift towards extremes using Welch's unequal variance t-test; the results of this comparison and of the tests are included in Figure 1 in the main paper. Overall distributions of the variables use values from grid cells which contain land, and with latitudes south of 60° S removed in order to best represent inhabited regions.

Step 2: Creation of hazard severity measure

After validating ERA-Interim meteorological data's coincidence of upper-/lower-percentile values with EM-DAT-listed disasters, a yearly measure of the frequency of extreme events in each country is introduced. We then define ERA-Interim values of the corresponding meteorological variable in terms of its place in its overall distribution as its percentile ranking over the 1981-2018 period; this is done individually for each grid cell in order to best represent its local climate. The percentile ranking is generated with the nearest-rank method, with the percentile P calculated using the ordinal rank of the meteorological variable n in the overall distribution of sample size N listed by increasing values, with $P = \frac{n}{N} \times 100$. The 1981-2018 distributions of each meteorological variable are used to calculate the number of days per year in which the values exceeded two standard deviations from the climatological mean within the boundaries of each administrative region at the country level. That is: for floods, the number of days per year with daily precipitation exceeding two standard deviations above the mean; for droughts, the number of days per year with 180-day accumulated precipitation exceeding two standard deviations below the mean; for storms, the number of days per year with maximum sustained wind speed exceeding two standard deviations above the mean; for heat waves, the number of days with daily maximum temperatures exceeding two standard deviations above the mean; for cold waves, the number of days with daily minimum temperatures exceeding two standard deviations below the mean. Shapefiles of the administrative regions used to mask ERA-Interim in this step were sourced from GADM (19).

These values are then divided by the number of data points (grid cells) available from ERA-Interim in each administrative region to normalize the measure across countries. The result is a record of measures of annual frequency of meteorological extremes in each administrative state, which is used in the regression analysis of UN disaster aid. This hazard severity measure is highly correlated with a dummy variable indicating floods (=1) (r=0.877, N=1,740, see Table S2). This is probably because floods are the most frequently occurring disaster type in the analysis, partially causing this high correlation. Almost 40 percent of the disasters we study are floods.

Social data collection and coding

The dataset is coded at the level of disasters, which are clustered in disaster types, countries, and years. See "Materials and Methods" in the main paper and Table S1 for an overview of all indicators and the level of analysis at which they are coded. Floods are the most frequently occurring disaster type in the analysis, that is, almost 40% of the disasters we study (followed by storms at 23%).

We coded aid flows to specific disasters that were either explicitly or implicitly linked to climate in UN documents. We consulted Central Emergency Relief Fund (CERF) documents, the Financial Tracking Service database, and where needed, media sources from reputable newspapers such as The Guardian, and individual project reporting sheets with more disaggregated numbers and purposes of spending. For example, in Guatemala, which experienced a drought in 2014, documents also mention riverine flooding, a tropical cyclone, and severe winter conditions (20, 21). In this case, we combined the aid estimated by the UN as required to meet humanitarian need, and the aid received for all of these occurrences in 2014, and divided them by five to match them to the five disasters reported in EM-DAT.

Based on this coding process, we created three variables described in the paper: immediate short-run aid through the CERF, long-term disaster reconstruction aid via the Country Based Pooled Funds (CBPF), and other bilateral and multilateral aid coordinated by the UN. The CERF complements the CBPF contributions by being able to more flexibly and quickly react to disasters. For example, in 2017 Ethiopia experienced the worst El Niño induced drought in 50 years, which affected mainly pastoralist communities in southern and eastern parts of the country. The drought was a result of two consecutive failed rainy seasons starting in 2016, and affected the livelihoods, food security, and health of about 4.6 million Ethiopians. In total 133 million funds could be raised, among them about 18,5 million from the CERF, 37,8 million from the Country-based Pool Funds, and 76,7 million from other bilateral or multilateral sources (22).

We complement these aid data with a number of indicators of hazard severity (Table 1 in the main paper), humanitarian need, and strategic interests for the main tables. For the robustness checks, we added disaster-level population density and country-level measures of Gross Domestic Product (GDP), trade in percent of GDP, and infant mortality. In terms of strategic variables, we include PTAs signed, former P5 colony, oil endowment, UN General Assembly (UNGA) voting in line with the United States (US), and an estimation of emergency Official Development Assistance (ODA) in the main tables. In the robustness checks, we add variables capturing if recipient countries are temporary UN Security Council (UNSC) members, recipients of IMF assistance, subject to US sanctions, and ideologically distant or close to the US in UNGA sessions.

The population density and emergency ODA indicators used require brief discussion. Population density is coded using geocoded disaster data (23) to extract area-weighted values for their population density from the Gridded Population of the World, Version 4, Revision 11 data set (24). The variable is coded at 2.5 arc-minute (roughly 5 km) resolution and matched to the disasters in our dataset by using the EM-DAT identifier or by averaging the observations at the level of disaster type. The most recent yearly data of the years 2000, 2005, 2010 and 2015 prior to the disaster were used; for a disaster in e.g. 2007, population density data from the 2005 census was used. The geocoded dataset was not generated in conjunction with our dataset and contains a selection of 2150 disasters in the categories of cold and heat waves, droughts, floods, and storms, which only partially overlaps with our dataset. We were able to match 1,145 observations for population density.

In terms of emergency ODA, we control for the fact that the UN and other bilateral or multilateral donors might in their disaster funding anticipate the amount of emergency ODA in each year (25). The allocation of ODA more generally has been shown to depend on specific variables, which is why we first regress emergency ODA in each country in each year on these determinants (GDP, corruption, state fragility, and affected people). The generalized residuals from this regression comprises the additional information on humanitarian funding that is not explained by these determinants, is then entered as explanatory variable into the models on CERF and bilateral funding. So, we include that part of humanitarian funding left unexplained by the variables included in our model, thereby avoiding multicollinearity and endogeneity (26).

Table S1. Variable descriptions

Variable	Description	Source
Variables in main models		
CERF aid	Disaster level clustered in countries and years. Total CERF aid in million USD in 2010 prices.	CERF documents at https://cerf.un.org/
CBPF aid	Disaster level clustered in countries and years. Total CBPF aid in million USD in 2010 prices.	Financial Tracking Service, CERF documents
Other bilateral and multilateral aid	Disaster level clustered in countries and years. Total amount of remaining aid not flowing through CERF and CBPF from all sources.	Financial Tracking Service, CERF documents
Hazard severity	Disaster and country level. The number of events per year within a country's borders which exceeds 2 standard deviations of normal levels, normalized by the number of grid cells that the country covers. In the case of floods, this corresponds to the number of days per grid cell where the daily precipitation anomaly exceeded 2 standard deviations (SPI_{1d} > 2.0, where SPI_{1d} refers to the standardized precipitation index for the scale of one day in standard deviations. In the case of droughts, this refers to the number of days per cell where the 180-day (6-month) accumulated precipitation anomaly SPI_{6m} was more than 2 standard deviations below the mean (SPI_{6m} < -2.0). For storms, this is the number of days per cell where the daily maximum sustained wind speed U_{max} exceeded 2 standard deviations above the mean ($\Delta U_{max} > 2\ \sigma$). Regarding extreme temperature, we distinguish between heat waves, where hazard severity is the number of days per cell where the daily maximum temperature at 2 m T_{max} exceeded 2 standard deviations above the mean ($\Delta T_{max} > 2\ \sigma$). For cold waves, this refers to the number of days per cell where the daily minimum temperature at 2 m T_{min} exceeded 2 standard deviations below the mean ($\Delta T_{min} < -2\ \sigma$).	(18, 23)
Total affected persons (log)	Disaster level, clustered in countries and years. Total number of affected people by a disaster (logarithmized).	(18)
State fragility index	Country level, coded yearly. Index based on variables in the following four categories: cohesion, social, economic, and political.	The Fund for Peace dataset at https://fragilestatesindex.org
PTAs signed	Country level. Number of preferential trade agreements (PTAs) signed by recipient state in a given year.	(27)
Former P5 colony	Country level. Dummy coded 1 if a country has been a former P5 colony since 1816, and 0 otherwise.	(28)
Oil endowment	Country level. The extrapolated variable *lnacorcount*, by unique country identifier and year. The measure expresses the natural logarithm of the total number of onshore oil	(29)

	and gas fields intersecting with a country's territory in 1982. Based on the new ACOR data.	
Emergency ODA (residual)	Country level. Generalized residuals from ordinary least squares regression of yearly emergency ODA on *GDP, corruption, state fragility,* and *affected people.*	(18, 30)
UNGA voting with the US	Country level. Voting similarity index between country and US in a given session, coded as the share of total votes of a recipient country aligned with the US in each session. During our observed time period, the dataset includes one session per country per year.	(31)
Conflict	Country level. Dummy coded 1 if the maximum intensity of armed internal conflict a government was involved in during a particular year, irrespective of conflict was minor or major (i.e., with more than 1000 deaths). 0 otherwise.	(32, 33)
Drought	Disaster level, clustered in countries and years. Dummy indicating 1 if a drought and 0 if otherwise.	(18)
Extreme temperature and co-occurring disasters	Disaster level, clustered in countries and years. Dummy indicating 1 if extreme heat waves or cold waves, and 0 if otherwise.	(18)
Flood	Disaster level, clustered in countries and years. Dummy indicating 1 if a coastal, flash or riverine flood, or other flood, and 0 if otherwise.	(18)
Storm	Disaster level, clustered in countries and years. Dummy indicating 1 if a convective storm, tropical cyclone, cyclone, extra-tropical storm, or other storm, and 0 if otherwise.	(18)
Variables in robustness checks		
Corruption	Country level. Corruption perception index in a given year.	Transparency International at https://www.transparency.org/research/cpi/overview
GDP per capita in PPP	Country level. GDP per capita in Purchasing Power Parity (PPP) in a given year.	World Development Indicator at https://data.worldbank.org/
Ideological distance to US	Country level. Absolute distance between a country and the US' respective ideal points, based on UNGA voting data in a given year.	(31)
IMF program	Country level. Dummy that is 1 if a country is partner to an IMF program in a given year, and 0 otherwise. IMF programs include Extended Fund Facility Arrangements, Exogenous Shock Facility Arrangements, Flexible Credit Line Arrangements, Precautionary Credit Line Arrangements, Precautionary and Liquidity Line Arrangement, Poverty Reduction and Growth Facility Arrangement, Standby Arrangement agreed.	(34)

Infant mortality	Country level. Number of infants dying before reaching one year of age, per 1,000 live births in a given year.	World Development Indicator at https://data.worldbank.org/
Population density	Disaster level, clustered in countries and years. Expressed in inhabitant per roughly 5 km resolution. Area-weighted values for population density at 2.5 arc-minute (roughly 5 km) resolution. The most recent data of the years 2000, 2005, 2010 and 2015 prior to a disaster were used.	(23, 24)
US sanctions	Country level. Dummy coded 1 if a country is subject to US sanctions in a given year and 0 otherwise.	(35)
Temporary UNSC member	Country level. Rotating seat in the UN Security Council (UNSC). Dummy that is 1 if the country is a temporary UNSC member in a given year and 0 otherwise.	(36, 37)
Trade in % of GDP	Country level. Total exports and imports as a percentage of GDP in a given year.	World Development Indicator at https://data.worldbank.org/

Notes: These variables are either included in the tables in the paper or the robustness checks in this Appendix. Listed in the order they occur.

Table S2. Correlations between independent variables in main models

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1. Hazard severity	1.000												
2. Total affected	0.239	1.000											
3. State fragility	-0.039	0.008	1.000										
4. PTAs signed	0.019	-0.027	-0.211	1.000									
5. P5 colony	0.030	0.041	0.063	0.000	1.000								
6. Oil endowment	-0.010	-0.021	-0.146	0.204	0.075	1.000							
7. Emergency ODA	-0.010	-0.002	-0.082	-0.001	0.113	-0.016	1.000						
8. UNGA voting with the US	0.005	-0.049	-0.122	-0.041	-0.019	0.005	-0.001	1.000					
9. Conflict	-0.008	-0.093	0.169	0.117	0.287	0.229	0.159	0.010	1.000				
10. Drought	-0.237	0.125	0.022	-0.022	-0.040	-0.087	-0.002	0.016	-0.050	1.000			
11. Ex. temperature and co-occurring disasters	-0.110	-0.140	-0.004	-0.023	-0.061	-0.016	0.112	0.071	0.066	-0.105	1.000		
12. Flood	0.877	0.244	-0.036	0.012	0.019	-0.006	-0.026	-0.016	0.001	-0.275	-0.301	1.000	
13. Storm	-0.303	0.034	-0.072	0.016	0.042	0.039	-0.047	-0.010	-0.030	-0.131	-0.143	-0.374	1.000

Notes: Pearson's correlation coefficients (*r*).These variables are either included in the tables in the paper or the robustness checks in this Appendix. Listed in the order they occur. *N*=1,740.

Table S3. Summary statistics

Variable	Min.	Mean	Max.	Std. Dev.	*N*
CERF aid	0.000	0.010	0.920	0.030	3,590
CBPF aid	0.000	0.030	8.040	0.290	3,590
Other bilateral and multilateral aid	0.000	0.000	0.550	0.020	3,590
Hazard severity	0.000	26.920	115.800	26.850	3,590
Total affected persons (log)	-6.910	0.380	12.710	4.660	3,590
State fragility index	17.000	74.830	115.000	23.410	2,652
PTAs signed	0.000	0.730	25.000	1.620	3,590
Former P5 colony	0.000	0.570	1.000	0.490	3,590
Oil endowment	0.000	2.050	8.890	2.260	3,241
Emergency ODA (residuals)	-2.160	-0.040	14.400	1.570	1,811
UNGA voting with the US	0.000	0.350	0.950	0.150	3,383
Conflict	0.000	0.150	1.000	0.360	3,590
Drought	0.000	0.080	1.000	0.260	3,590
Extreme temperature and co-occurring disasters	0.000	0.110	1.000	0.310	3,590
Flood	0.000	0.400	1.000	0.490	3,590
Storm	0.000	0.220	1.000	0.410	3,590
GDP per capita in PPP (log)	6.150	8.830	11.400	1.210	3,397
Trade in % of GDP	0.000	72.060	434.000	38.970	3,348
Infant mortality	2.600	45.550	216.800	43.640	3,511
Corruption perception index	1.000	17.110	91.000	20.740	3,362
Population density (log)	-2.920	4.800	9.620	1.580	1,299
Temporary UNSC membership	1.000	1.070	2.000	0.250	3,590
IMF assistance	0.000	0.090	1.000	0.280	3,093
US sanctions	0.000	0.160	1.000	0.370	3,590
Ideological distance from the US	0.000	2.740	4.810	1.020	3,590

Notes: These variables are either included in the tables in the paper or the robustness checks in this Appendix. Listed in the order they occur.

Robustness checks

Table S4. Tobit regression analysis of UN aid, including GDP per capita. Constant included but not reported. *p*-values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber-White) standard errors, clustered at the level of countries. * *p*<.05, ** *p*<.01.

	Immediate short-run disaster aid through CERF (log)	Long-run disaster reconstruction aid through CBPF (log)	Other bilateral and multilateral funds coordinated by the UN (log)
Needs-related factors			
Hazard severity	0.001	0.013***	0.002**
	(0.173)	(0.001)	(0.003)
Total affected persons (log)	0.003**	0.034*	-0.001
	(0.002)	(0.016)	(0.783)
State fragility index	0.001***	0.030***	0.006**
	(0.001)	(0.000)	(0.003)
GDP per capita in PPP (log)	-0.018*	0.038	-0.024
	(0.013)	(0.662)	(0.360)
Strategic factors			
PTAs signed	-0.001	-0.105	-0.016
	(0.821)	(0.391)	(0.634)
Former P5 colony	-0.009	-0.133	0.036
	(0.353)	(0.409)	(0.313)
Oil endowment	-0.004	-0.103	-0.004
	(0.344)	(0.195)	(0.792)
Emergency ODA (residuals)	0.006*	0.143***	0.018***
	(0.012)	(0.000)	(0.000)
UNGA voting with the US	-0.055	2.588***	0.463*
	(0.091)	(0.001)	(0.021)
Controls:			
Conflict	0.014	-0.033	0.056
	(0.422)	(0.914)	(0.289)
Drought	0.090***	1.069***	0.196**
	(0.000)	(0.001)	(0.003)
Extreme temperature and co-occurring disasters	0.086***	1.052**	0.194**
	(0.000)	(0.004)	(0.004)
Flood	0.007	-0.254	-0.008
	(0.770)	(0.279)	(0.824)
Storm	0.037**	0.223	0.033
	(0.007)	(0.286)	(0.533)
Number of observations	1731	1731	1731
Bayesian Information Criterion	52.927	1169.127	310.887
Log likelihood	33.188	-524.912	-95.792

Table S5. Tobit regression analysis of UN aid, including trade openness. Constant included but not reported. *p*-values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber-White) standard errors, clustered at the level of countries. * *p*<.05, ** *p*<.01.

	Immediate short-run disaster aid through CERF (log)	Long-run disaster reconstruction aid through CBPF (log)	Other bilateral and multilateral funds coordinated by the UN (log)
Needs-related factors			
Hazard severity	0.001	0.013**	0.002**
	(0.153)	(0.001)	(0.003)
Total affected persons (log)	0.003**	0.029*	-0.001
	(0.003)	(0.027)	(0.740)
State fragility index	0.002***	0.026***	0.005**
	(0.000)	(0.000)	(0.007)
Trade in % of GDP	-0.000	-0.003	-0.001*
	(0.062)	(0.287)	(0.013)
Strategic factors			
PTAs signed	-0.001	-0.092	-0.014
	(0.849)	(0.421)	(0.688)
Former P5 colony	-0.011	-0.145	0.034
	(0.280)	(0.347)	(0.351)
Oil endowment	-0.010*	-0.093	-0.017
	(0.015)	(0.164)	(0.292)
Emergency ODA (residuals)	0.005*	0.143***	0.018***
	(0.028)	(0.000)	(0.000)
UNGA voting with the US	-0.070*	2.425***	0.462*
	(0.045)	(0.001)	(0.029)
Controls:			
Conflict	0.009	-0.140	0.039
	(0.615)	(0.654)	(0.500)
Drought	0.089***	1.029***	0.198**
	(0.000)	(0.001)	(0.004)
Extreme temperature and co-occurring disasters	0.086***	0.921**	0.190**
	(0.000)	(0.005)	(0.006)
Flood	0.001	-0.295	-0.021
	(0.973)	(0.225)	(0.557)
Storm	0.037**	0.206	0.030
	(0.007)	(0.301)	(0.576)
Number of observations	1684	1684	1684
Bayesian Information Criterion	92.877	1121.545	301.454
Log likelihood	12.993	-501.341	-91.296

Table S6. Tobit regression analysis of UN aid, including infant mortality. Constant included but not reported. *p*-values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber-White) standard errors, clustered at the level of countries. * *p*<.05, ** *p*<.01.

	Immediate short-run disaster aid through CERF (log)	Long-run disaster reconstruction aid through CBPF (log)	Other bilateral and multilateral funds coordinated by the UN (log)
Needs-related factors			
Hazard severity	0.001	0.013***	0.002**
	(0.176)	(0.001)	(0.002)
Total affected persons (log)	0.003**	0.034*	-0.001
	(0.002)	(0.016)	(0.823)
State fragility index	0.002***	0.033***	0.006**
	(0.000)	(0.001)	(0.002)
Infant mortality	0.000	-0.003	0.000
	(0.398)	(0.180)	(0.749)
Strategic factors			
PTAs signed	-0.001	-0.105	-0.014
	(0.813)	(0.389)	(0.671)
Former P5 colony	-0.010	-0.147	0.035
	(0.345)	(0.354)	(0.341)
Oil endowment	-0.009*	-0.103	-0.012
	(0.038)	(0.155)	(0.426)
Emergency ODA (residuals)	0.005*	0.153***	0.017***
	(0.035)	(0.000)	(0.000)
UNGA voting with the US			
	-0.067*	2.541***	0.452*
Controls:	(0.049)	(0.001)	(0.028)
Conflict	0.017	-0.056	0.062
	(0.310)	(0.856)	(0.242)
Drought	0.091***	1.063***	0.198**
	(0.000)	(0.001)	(0.003)
Extreme temperature and co-occurring disasters	0.088***	1.052**	0.195**
	(0.000)	(0.003)	(0.004)
Flood	0.006	-0.259	-0.012
	(0.798)	(0.276)	(0.747)
Storm	0.038**	0.207	0.035
	(0.006)	(0.318)	(0.521)
Number of observations	1731	1731	1731
Bayesian Information Criterion	68.120	1166.611	312.119
Log likelihood	25.592	-523.654	-96.408

Table S7. Tobit regression analysis of UN aid, including corruption. Constant included but not reported. *p*-values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber-White) standard errors, clustered at the level of countries. * *p*<.05, ** *p*<.01.

	Immediate short-run disaster aid through CERF (log)	Long-run disaster reconstruction aid through CBPF (log)	Other bilateral and multilateral funds coordinated by the UN (log)
Needs-related factors			
Hazard severity	0.001	0.012***	0.002**
	(0.163)	(0.001)	(0.003)
Total affected persons (log)	0.003**	0.035*	-0.001
	(0.003)	(0.014)	(0.787)
State fragility index	0.002***	0.032***	0.006**
	(0.000)	(0.000)	(0.003)
Corruption	-0.001**	0.007	-0.000
	(0.006)	(0.078)	(0.681)
Strategic factors			
PTAs signed	-0.005	-0.061	-0.017
	(0.402)	(0.615)	(0.582)
Former P5 colony	-0.010	-0.141	0.035
	(0.348)	(0.388)	(0.340)
Oil endowment	-0.009*	-0.094	-0.012
	(0.037)	(0.193)	(0.421)
Emergency ODA (residuals)	0.005*	0.148***	0.017***
	(0.029)	(0.000)	(0.000)
UNGA voting with the US	-0.050	2.485***	0.458*
	(0.150)	(0.001)	(0.026)
Controls:			
Conflict	0.018	-0.058	0.062
	(0.280)	(0.850)	(0.239)
Drought	0.092***	1.048***	0.199**
	(0.000)	(0.001)	(0.003)
Extreme temperature and co-occurring disasters	0.088***	1.059**	0.196**
	(0.000)	(0.004)	(0.004)
Flood	0.005	-0.249	-0.013
	(0.838)	(0.295)	(0.729)
Storm	0.037**	0.213	0.035
	(0.005)	(0.301)	(0.516)
Number of observations	1731	1731	1731
Bayesian Information Criterion	55.698	1164.433	312.045
Log likelihood	31.803	-522.565	-96.371

Table S8. Tobit regression analysis of UN aid, including population density. Constant included but not reported. *p*-values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber-White) standard errors, clustered at the level of countries. * *p*<.05, ** *p*<.01.

	Immediate short-run disaster aid through CERF (log)	Long-run disaster reconstruction aid through CBPF (log)	Other bilateral and multilateral funds coordinated by the UN (log)
Needs-related factors			
Hazard severity	-0.000	0.006*	0.001
	(0.384)	(0.027)	(0.176)
Total affected persons (log)	0.003***	0.041	-0.002
	(0.000)	(0.112)	(0.609)
State fragility index	0.002***	0.032**	0.007**
	(0.000)	(0.002)	(0.008)
Population density (log)	-0.006*	-0.077	0.008
	(0.012)	(0.136)	(0.416)
Strategic factors			
PTAs signed	0.002	-0.065	0.011
	(0.692)	(0.607)	(0.583)
Former P5 colony	0.001	-0.121	0.025
	(0.889)	(0.498)	(0.512)
Oil endowment	-0.008*	-0.104	-0.005
	(0.012)	(0.127)	(0.653)
Emergency ODA (residuals)	0.005***	0.145***	0.012***
	(0.000)	(0.000)	(0.000)
UNGA voting with the US	-0.069*	2.680**	0.416
	(0.027)	(0.004)	(0.061)
Controls:			
Conflict	0.013	-0.269	-0.019
	(0.318)	(0.307)	(0.594)
Drought	-0.040*	-0.626	0.032
	(0.012)	(0.084)	(0.506)
Extreme temperature and co-occurring disasters	-0.021	-0.341	-0.008
	(0.150)	(0.138)	(0.798)
Flood	-0.067***	-1.371***	-0.114*
	(0.000)	(0.001)	(0.014)
Storm	-0.064***	-1.119**	-0.106*
	(0.000)	(0.002)	(0.048)
Number of observations	816	816	816
Bayesian Information Criterion	-241.589	680.973	178.677
Log likelihood	174.430	-286.851	-35.703

Table S9. Tobit regression analysis of UN aid, controlling for a product term between total affected persons and hazard severity. Constant included but not reported. *p*-values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber-White) standard errors, clustered at the level of countries. * *p*<.05, ** *p*<.01.

	Immediate short-run disaster aid through CERF (log)	Long-run disaster reconstruction aid through CBPF (log)	Other bilateral and multilateral funds coordinated by the UN (log)
Needs-related factors			
Hazard severity	0.000	0.012**	0.002**
	(0.253)	(0.001)	(0.003)
Total affected persons (log)	0.000	0.021	-0.004
	(0.660)	(0.238)	(0.177)
Total affected persons (log) * hazard severity	0.000	0.000	0.000
	(0.062)	(0.331)	(0.141)
State fragility index	0.002***	0.029***	0.007**
	(0.000)	(0.000)	(0.003)
Strategic factors			
PTAs signed	-0.001	-0.101	-0.011
	(0.825)	(0.408)	(0.729)
Former P5 colony	-0.010	-0.128	0.035
	(0.330)	(0.428)	(0.353)
Oil endowment	-0.010*	-0.094	-0.013
	(0.025)	(0.190)	(0.392)
Emergency ODA (residuals)	0.006*	0.144***	0.018***
	(0.021)	(0.000)	(0.000)
UNGA voting with the US	-0.069*	2.622***	0.456*
	(0.043)	(0.001)	(0.026)
Controls:			
Conflict	0.017	-0.039	0.061
	(0.329)	(0.898)	(0.244)
Drought	0.099***	1.116***	0.211**
	(0.000)	(0.001)	(0.002)
Extreme temperature and co-occurring disasters	0.093***	1.070**	0.202**
	(0.000)	(0.003)	(0.003)
Flood	0.008	-0.242	-0.009
	(0.729)	(0.306)	(0.802)
Storm	0.044**	0.257	0.043
	(0.002)	(0.226)	(0.438)
Number of observations	1731	1731	1731
Bayesian Information Criterion	56.273	1168.149	310.242
Log likelihood	31.515	-524.423	-95.469

Table S10. Tobit regression analysis of CERF aid, entering strategic factors separately. Constant included but not reported. *p*-values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber-White) standard errors, clustered at the level of countries. * p<.05, ** p<.01.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Needs-related factors						
Hazard severity	0.001	0.001	0.001	0.001	0.001	0.001
	(0.192)	(0.187)	(0.192)	(0.195)	(0.188)	(0.175)
Total affected persons (log)	0.003**	0.003**	0.003**	0.002*	0.003**	0.003**
	(0.007)	(0.005)	(0.002)	(0.011)	(0.009)	(0.002)
State fragility index	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Strategic factors						
PTAs signed	-0.005					-0.002
	(0.360)					(0.776)
Former P5 colony		-0.008				-0.010
		(0.497)				(0.318)
Oil endowment			-0.010*			-0.009*
			(0.025)			(0.029)
Emergency ODA (residuals)				0.006*		0.006*
				(0.024)		(0.020)
UNGA voting with the US					-0.069*	-0.072*
					(0.045)	(0.037)
Controls						
Conflict	0.009	0.010	0.019	0.001	0.007	0.017
	(0.614)	(0.550)	(0.280)	(0.959)	(0.667)	(0.310)
Drought	0.099***	0.099***	0.091***	0.098***	0.101***	0.090***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Extreme temperature and co-occurring	0.099***	0.099***	0.093***	0.095***	0.101***	0.088***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Flood	0.011	0.011	0.008	0.012	0.011	0.006
	(0.637)	(0.651)	(0.746)	(0.599)	(0.632)	(0.797)
Storm	0.039**	0.039**	0.036**	0.040**	0.039**	0.037**
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.006)
Number of observations	1731	1731	1731	1731	1731	1731
Bayesian Information Criterion	82.647	83.004	56.033	68.847	77.912	62.026
Log likelihood	-0.313	-0.491	12.994	6.587	2.055	24.910

Table S11. Tobit regression analysis of CBPF aid, entering strategic factors separately. Constant included but not reported. *p*-values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber-White) standard errors, clustered at the level of countries. * *p*<.05, ** *p*<.01.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Needs-related factors						
Hazard severity	0.013***	0.013***	0.013***	0.013**	0.013***	0.012***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Total affected persons (log)	0.034*	0.035*	0.036*	0.030*	0.036*	0.033*
	(0.025)	(0.021)	(0.013)	(0.039)	(0.017)	(0.017)
State fragility index	0.032***	0.034***	0.030***	0.029***	0.036***	0.029***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Strategic factors						
PTAs signed	-0.183					-0.105
	(0.196)					(0.392)
Former P5 colony		-0.050				-0.130
		(0.775)				(0.423)
Oil endowment			-0.121			-0.092
			(0.121)			(0.199)
Emergency ODA (residuals)				0.139***		0.144***
				(0.001)		(0.000)
UNGA voting with the US					2.840***	2.610***
					(0.000)	(0.001)
Controls:						
Conflict	0.009	-0.011	0.117	-0.184	-0.049	-0.040
	(0.978)	(0.971)	(0.723)	(0.503)	(0.870)	(0.894)
Drought	1.261**	1.261**	1.156***	1.213**	1.231**	1.070***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Extreme temperature and co-occurring disasters	1.350**	1.357**	1.278**	1.202**	1.307**	1.050**
	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.004)
Flood	-0.247	-0.249	-0.264	-0.198	-0.260	-0.248
	(0.316)	(0.307)	(0.280)	(0.413)	(0.296)	(0.292)
Storm	0.242	0.235	0.209	0.265	0.223	0.224
	(0.283)	(0.296)	(0.327)	(0.226)	(0.320)	(0.281)
Number of observations	1731	1731	1731	1731	1731	1731
Bayesian Information Criterion	1212.889	1217.610	1205.523	1181.196	1184.395	1161.896
Log likelihood	-565.434	-567.795	-561.751	-549.588	-551.187	-525.025

Table S12. Tobit regression analysis of other bilateral and multilateral aid, entering strategic factors separately. Constant included but not reported. *p*-values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber-White) standard errors, clustered at the level of countries. * *p*<.05, ** *p*<.01.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Needs-related factors						
Hazard severity	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)
Total affected persons (log)	0.001	0.001	0.001	0.000	0.001	-0.000
	(0.625)	(0.708)	(0.671)	(0.933)	(0.667)	(0.835)
State fragility index	0.008**	0.008***	0.007***	0.006**	0.008***	0.006**
	(0.002)	(0.001)	(0.001)	(0.005)	(0.000)	(0.003)
Strategic factors						
PTAs signed	-0.032					-0.014
	(0.364)					(0.678)
Former P5 colony		0.050				0.035
		(0.196)				(0.350)
Oil endowment			-0.017			-0.012
			(0.309)			(0.417)
Emergency ODA (residuals)				0.019***		0.018***
				(0.000)		(0.000)
UNGA voting with the US					0.477*	0.450*
					(0.016)	(0.027)
Controls:						
Conflict	0.086	0.062	0.100	0.058	0.081	0.061
	(0.108)	(0.196)	(0.077)	(0.252)	(0.103)	(0.244)
Drought	0.218**	0.218**	0.197**	0.213**	0.214**	0.197**
	(0.009)	(0.009)	(0.007)	(0.009)	(0.010)	(0.003)
Extreme temperature and co-occurring disasters	0.248**	0.247**	0.230**	0.222**	0.234**	0.196**
	(0.004)	(0.003)	(0.002)	(0.009)	(0.003)	(0.004)
Flood	-0.015	-0.013	-0.015	-0.008	-0.020	-0.013
	(0.730)	(0.762)	(0.711)	(0.850)	(0.613)	(0.725)
Storm	0.035	0.034	0.030	0.040	0.030	0.035
	(0.510)	(0.531)	(0.564)	(0.504)	(0.585)	(0.525)
Number of observations	1731	1731	1731	1731	1731	1731
Bayesian Information Criterion	316.256	315.342	314.834	297.767	301.250	304.797
Log likelihood	-117.118	-116.661	-116.406	-107.873	-109.615	-96.475

Table S13. Tobit regression analysis of UN aid, controlling for temporary membership in the UN Security Council. Constant included but not reported. *p*-values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber-White) standard errors, clustered at the level of countries. * *p*<.05, ** *p*<.01.

	Immediate short-run disaster aid through CERF (log)	Long-run disaster reconstruction aid through CBPF (log)	Other bilateral and multilateral funds coordinated by the UN (log)
Needs-related factors			
Hazard severity	0.001	0.013***	0.002**
	(0.172)	(0.001)	(0.002)
Total affected persons (log)	0.003**	0.035*	-0.000
	(0.002)	(0.017)	(0.948)
State fragility index	0.002***	0.030***	0.007**
	(0.000)	(0.000)	(0.002)
Strategic factors			
PTAs signed	-0.002	-0.105	-0.015
	(0.715)	(0.392)	(0.667)
Former P5 colony	-0.010	-0.123	0.037
	(0.333)	(0.451)	(0.326)
Oil endowment	-0.010*	-0.101	-0.017
	(0.027)	(0.175)	(0.318)
Emergency ODA (residuals)	0.006*	0.145***	0.018***
	(0.020)	(0.000)	(0.000)
UNGA voting with the US	-0.072*	2.601***	0.426*
	(0.035)	(0.001)	(0.034)
Temporary UNSC membership	0.021	0.341	0.112*
	(0.191)	(0.209)	(0.027)
Controls:			
Conflict	0.017	-0.067	0.054
	(0.318)	(0.823)	(0.304)
Drought	0.091***	1.077***	0.205**
	(0.000)	(0.001)	(0.001)
Extreme temperature and co-occurring disasters	0.088***	1.056**	0.203**
	(0.000)	(0.004)	(0.003)
Flood	0.006	-0.246	-0.007
	(0.797)	(0.300)	(0.845)
Storm	0.038**	0.232	0.047
	(0.005)	(0.270)	(0.379)
Number of observations	1731	1731	1731
Bayesian Information Criterion	66.314	1166.537	305.964
Log likelihood	26.494	-523.617	-93.330

Table S14. Tobit regression analysis of UN aid, controlling for IMF assistance in a recipient country. Constant included but not reported. *p*-values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber-White) standard errors, clustered at the level of countries. * *p*<.05, ** *p*<.01.

	Immediate short-run disaster aid through CERF (log)	Long-run disaster reconstruction aid through CBPF (log)	Other bilateral and multilateral funds coordinated by the UN (log)
Needs-related factors			
Hazard severity	0.001	0.014***	0.002**
	(0.208)	(0.000)	(0.006)
Total affected persons (log)	0.003**	0.029	-0.001
	(0.004)	(0.074)	(0.636)
State fragility index	0.002***	0.032***	0.006**
	(0.000)	(0.000)	(0.006)
Strategic factors			
PTAs signed	-0.004	-0.156	-0.007
	(0.555)	(0.294)	(0.770)
Former P5 colony	-0.010	-0.139	0.029
	(0.355)	(0.442)	(0.381)
Oil endowment	-0.009*	-0.089	-0.008
	(0.046)	(0.241)	(0.514)
Emergency ODA (residuals)	0.005*	0.144***	0.013***
	(0.032)	(0.000)	(0.000)
UNGA voting with the US	-0.076	3.307***	0.461*
	(0.065)	(0.001)	(0.029)
IMF assistance	0.010	0.036	0.035
	(0.448)	(0.856)	(0.292)
Controls:			
Conflict	0.019	0.036	0.038
	(0.310)	(0.912)	(0.386)
Drought	0.087***	1.120**	0.162**
	(0.000)	(0.001)	(0.004)
Extreme temperature and co-occurring disasters	0.085***	1.052**	0.137**
	(0.000)	(0.009)	(0.006)
Flood	0.008	-0.236	-0.000
	(0.762)	(0.354)	(0.997)
Storm	0.042**	0.254	0.038
	(0.005)	(0.306)	(0.383)
Number of observations	1448	1448	1448
Bayesian Information Criterion	61.519	1030.336	248.073
Log likelihood	27.464	-456.944	-65.813

Table S15. Tobit regression analysis of UN aid, controlling for US sanctions. Constant included but not reported. *p*-values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber-White) standard errors, clustered at the level of countries. * *p*<.05, ** *p*<.01.

	Immediate short-run disaster aid through CERF (log)	Long-run disaster reconstruction aid through CBPF (log)	Other bilateral and multilateral funds coordinated by the UN (log)
Needs-related factors			
Hazard severity	0.001	0.012***	0.002**
	(0.168)	(0.001)	(0.003)
Total affected persons (log)	0.003**	0.033*	-0.000
	(0.002)	(0.017)	(0.846)
State fragility index	0.002***	0.029***	0.006**
	(0.000)	(0.000)	(0.004)
Strategic factors			
PTAs signed	-0.002	-0.104	-0.014
	(0.772)	(0.397)	(0.673)
Former P5 colony	-0.011	-0.126	0.036
	(0.291)	(0.429)	(0.334)
Oil endowment	-0.009*	-0.091	-0.012
	(0.021)	(0.198)	(0.451)
Emergency ODA (residuals)	0.006*	0.144***	0.018***
	(0.021)	(0.000)	(0.000)
UNGA voting with the US	-0.070*	2.591***	0.440*
	(0.050)	(0.001)	(0.032)
US sanctions	0.004	-0.035	-0.019
	(0.758)	(0.833)	(0.622)
Controls:			
Conflict	0.018	-0.046	0.058
	(0.259)	(0.878)	(0.273)
Drought	0.090***	1.070***	0.197**
	(0.000)	(0.001)	(0.002)
Extreme temperature and co-occurring disasters	0.088***	1.047**	0.195**
	(0.000)	(0.004)	(0.004)
Flood	0.006	-0.247	-0.012
	(0.803)	(0.296)	(0.759)
Storm	0.037**	0.223	0.034
	(0.006)	(0.282)	(0.529)
Number of observations	1731	1731	1731
Bayesian Information Criterion	69.243	1169.296	312.000
Log likelihood	25.030	-524.996	-96.348

Table S16. Tobit regression analysis of UN aid, including a temporal trend variable. Constant included but not reported. *p*-values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber-White) standard errors, clustered at the level of countries. * *p*<.05, ** *p*<.01.

	Immediate short-run disaster aid through CERF (log)	Long-run disaster reconstruction aid through CBPF (log)	Other bilateral and multilateral funds coordinated by the UN (log)
Needs-related factors			
Hazard severity	0.001	0.012***	0.002**
	(0.146)	(0.001)	(0.002)
Total affected persons (log)	0.003**	0.035*	-0.000
	(0.003)	(0.013)	(0.884)
State fragility index	0.002***	0.029***	0.006**
	(0.000)	(0.000)	(0.003)
Strategic factors			
PTAs signed	-0.006	-0.052	-0.010
	(0.354)	(0.663)	(0.751)
Former P5 colony	-0.009	-0.156	0.033
	(0.380)	(0.338)	(0.361)
Oil endowment	-0.009*	-0.098	-0.013
	(0.040)	(0.175)	(0.401)
Emergency ODA (residuals)	0.005*	0.151***	0.018***
	(0.031)	(0.000)	(0.000)
UNGA voting with the US	-0.024	2.242**	0.427*
	(0.529)	(0.003)	(0.040)
Controls:			
Conflict	0.018	-0.042	0.061
	(0.291)	(0.894)	(0.243)
Drought	0.092***	1.051***	0.195**
	(0.000)	(0.001)	(0.002)
Extreme temperature and co-occurring disasters	0.087***	1.062**	0.196**
	(0.000)	(0.003)	(0.004)
Flood	0.003	-0.241	-0.013
	(0.890)	(0.313)	(0.727)
Storm	0.038**	0.196	0.033
	(0.005)	(0.332)	(0.548)
Trend	0.004***	-0.045*	-0.003
	(0.001)	(0.013)	(0.562)
Number of observations	1731	1731	1731
Bayesian Information Criterion	53.702	1162.229	311.878
Log likelihood	32.801	-521.463	-96.287

Table S17. Cross-sectional logistic regression analysis of receiving UN aid (=1). Constant included but not reported. *p*-values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber-White) standard errors, clustered at the level of countries. * *p*<.05, ** *p*<.01.

	Immediate short-run disaster aid through CERF (log)	Long-run disaster reconstruction aid through CBPF (log)	Other bilateral and multilateral funds coordinated by the UN (log)
Needs-related factors			
Hazard severity	0.018***	0.027***	0.028***
	(0.000)	(0.000)	(0.000)
Total affected persons (log)	0.049**	0.039	0.002
	(0.003)	(0.065)	(0.948)
State fragility index	0.043***	0.043***	0.072***
	(0.000)	(0.000)	(0.000)
Strategic factors			
PTAs signed	-0.095	-0.336*	-0.263
	(0.346)	(0.043)	(0.324)
Former P5 colony	-0.122	-0.011	0.254
	(0.402)	(0.953)	(0.433)
Oil endowment	-0.263***	-0.150*	-0.044
	(0.000)	(0.012)	(0.668)
Emergency ODA (residuals)	0.070	0.133**	0.271***
	(0.097)	(0.006)	(0.000)
UNGA voting with the US	-1.962**	4.580***	5.459***
	(0.002)	(0.000)	(0.000)
Controls:			
Conflict	0.290	-0.308	0.438
	(0.154)	(0.259)	(0.212)
Drought	2.169***	1.864***	2.174***
	(0.000)	(0.000)	(0.001)
Extreme temperature and co-occurring disasters	2.478***	1.727***	2.393***
	(0.000)	(0.000)	(0.000)
Flood	0.190	-0.570	-0.251
	(0.605)	(0.222)	(0.736)
Storm	1.085***	0.455	0.322
	(0.000)	(0.264)	(0.694)
Number of observations	1731	1731	1731
Bayesian Information Criterion	1512.928	1016.292	494.637
Log likelihood	-704.269	-455.951	-195.123

Table S18. Time-series cross-sectional logistic regression analysis of receiving UN aid (=1) with fixed effects. Constant included but not reported. *p*-values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber-White) standard errors, clustered at the level of countries. * $p<.05$, ** $p<.01$.

	Immediate short-run disaster aid through CERF (log)	Long-run disaster reconstruction aid through CBPF (log)	Other bilateral and multilateral funds coordinated by the UN (log)
Needs-related factors			
Hazard severity	0.020***	0.023***	0.026**
	(0.000)	(0.000)	(0.002)
Total affected persons (log)	0.044*	0.035	-0.014
	(0.010)	(0.108)	(0.674)
State fragility index	0.047***	0.038***	0.062***
	(0.000)	(0.000)	(0.000)
Strategic factors			
PTAs signed	-0.218	-0.243	-0.194
	(0.059)	(0.207)	(0.598)
Former P5 colony	-0.079	-0.152	0.258
	(0.598)	(0.428)	(0.452)
Oil endowment	-0.241***	-0.198**	-0.133
	(0.000)	(0.002)	(0.239)
Emergency ODA (residuals)	0.065	0.168**	0.303***
	(0.138)	(0.003)	(0.000)
UNGA voting with the US	-0.502	0.442	-0.057
	(0.636)	(0.740)	(0.982)
Controls:			
Conflict	0.286	-0.198	0.676
	(0.170)	(0.497)	(0.084)
Drought	2.209***	1.823***	2.212**
	(0.000)	(0.000)	(0.002)
Extreme temperature and co-occurring disasters	2.467***	1.778***	2.327***
	(0.000)	(0.000)	(0.001)
Flood	0.103	-0.348	0.006
	(0.785)	(0.471)	(0.994)
Storm	1.122***	0.527	0.215
	(0.000)	(0.201)	(0.810)
Number of observations	1731	1260	1260
Bayesian Information Criterion	1378.863	859.980	394.680
Log likelihood	-640.965	-383.587	-150.937

Table S19. Tobit regression analysis of UN aid, including lags. Constant included but not reported. *p*-values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber-White) standard errors, clustered at the level of countries. * p<.05, ** p<.01.

	Immediate short-run disaster aid through UN CERF (log)	Long-run disaster reconstruction aid through UN CBPF (log)	Long-run disaster reconstruction aid other bilateral and multilateral funds raised by the UN (log)
Needs-related factors			
Hazard severity	0.001	0.011**	0.002*
	(0.239)	(0.003)	(0.014)
Total affected persons (log)	0.002**	0.027*	-0.000
	(0.007)	(0.030)	(0.958)
State fragility index (lag 1)	0.002***	0.031***	0.006**
	(0.000)	(0.000)	(0.002)
Strategic factors			
PTAs signed (lag 1)	0.001	-0.024	-0.022
	(0.912)	(0.741)	(0.357)
Former P5 colony	-0.010	-0.125	0.031
	(0.336)	(0.438)	(0.395)
Oil endowment (lag 1)	-0.009*	-0.105	-0.014
	(0.031)	(0.155)	(0.360)
Emergency ODA (residuals) (lag 1)	0.006	0.134***	0.016***
	(0.052)	(0.001)	(0.000)
UNGA voting with US	-0.091**	2.309**	0.407*
	(0.008)	(0.001)	(0.019)
Controls:			
Conflict (lag 1)	0.016	-0.036	0.079
	(0.358)	(0.908)	(0.160)
Drought	0.092***	1.147***	0.201**
	(0.000)	(0.000)	(0.001)
Extreme temperature and co-occurring disasters	0.093***	1.086**	0.209**
	(0.000)	(0.002)	(0.002)
Flood	0.011	-0.177	0.000
	(0.671)	(0.482)	(0.994)
Storm	0.040**	0.226	0.032
	(0.003)	(0.292)	(0.568)
Number of observations	1644	1644	1644
Bayesian Information Criterion	51.824	1148.720	303.317
Log likelihood	29.625	-518.824	-96.122

Table S20. AUROC scores from out-of-sample cross validations.

	Immediate short-run disaster aid through CERF (log)	Long-run disaster reconstruction aid through CBPF (log)	Other bilateral and multilateral funds coordinated by the UN (log)
Baseline	0.691	0.701	0.768
Baseline + strategic	0.734	0.739	0.806
Baseline + needs	0.759	0.760	0.846
Baseline + needs + strategic	0.773	0.785	0.860

Notes: As the main regression analysis presented is limited in its information about the degree to which groups of variables (related to needs and strategic interests, respectively) contribute to predicting UN disaster aid, we conduct a series of additional tests that directly estimate the contribution of the different groups of explanatory factors through predictive modeling. Similar to regression modeling, this prediction approach cannot be used to estimate causal effects, but it can serve to test observable implications of relevant theories (1). Models that perform well out of sample on new data can be assumed to be able to capture relevant actual processes. In contrast, estimated relations in-sample that fail to predict similar outcomes on new data could reflect overfitting or misspecification of the original model or causal processes that are unique to the study sample.

Specifically, we conducted a set of 5-fold cross-validations. To this end, we partitioned the global sample of observations into five folds of equal size and then sequentially created training samples consisting of four of the folds and a test sample containing the last, fifth, fold. As most variables are measured at the level of countries and not disasters, we cluster disaster observations by country and year in the division of test and training samples. To improve the stability of the simulations, we replaced the Tobit estimator with conventional logit using a binary dependent variable indicating whether a country experiencing disasters received aid in a given year '1' or not '0' (see also Table S16 and S17).

Using randomized draws we repeated this 5-fold cross-validation ten times, resulting in 50 out-of-sample simulations. We estimated and then predicted four models for each of the dependent variables. First, we estimate a *baseline* model with control variables only. The baseline model is then extended in different ways: a model that adds *strategic* variables, a model with *needs-related* variables, and the full combined model including *strategic+needs-related* variables (variables included mirroring analyses presented in Table 2 in the main manuscript).

The table displays the average results of these 50 cross-validations by means of area under the curve for Receiver Operating Characteristic (AUROC). AUROC measures the area under the ROC curve, which plots the true positive rate over the true negative rate and varies between 0 (no correct predictions) and 1 (all correct predictions). AUROC scores are thus high for models that correctly recall a large fraction of the positives for any given level of falsely predicted aid allocation. It is thus a metric that is the closer to 1, the better the model is at correctly distinguishing between the two outcomes no aid received and aid received.

We find that across dependent variables, the *needs* model predicts better out of sample than the *strategic* model. While the combined model performs best, the improvement over the more parsimonious *needs* model is comparatively small, especially for disaster aid going via *other bilateral and multilateral funds in the UN*. Taken together, these additional tests provide further support of our argument about the relative importance of the themes we evaluate. Specifically, they indicate that need is a better predictor for UN disaster aid allocation than strategic explanations. That said, strategic explanations matter too as the full model gets the highest score.

Table S21. Tobit regression analysis of UN aid, controlling for ideological distance of the recipient country from the US in the UNGA. Constant included but not reported. *p*-values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber-White) standard errors, clustered at the level of countries. * *p*<.05, ** *p*<.01.

	Immediate short-run disaster aid through CERF (log)	Long-run disaster reconstruction aid through CBPF (log)	Other bilateral and multilateral funds coordinated by the UN (log)
Needs-related factors			
Hazard severity	0.001	0.013***	0.002**
	(0.187)	(0.001)	(0.004)
Total affected persons (log)	0.003**	0.033*	-0.000
	(0.002)	(0.021)	(0.974)
State fragility index	0.002***	0.028***	0.007**
	(0.000)	(0.000)	(0.003)
Strategic factors			
PTAs signed	-0.001	-0.115	-0.018
	(0.863)	(0.349)	(0.584)
Former P5 colony	-0.010	-0.118	0.049
	(0.302)	(0.468)	(0.187)
Oil endowment	-0.009*	-0.097	-0.011
	(0.028)	(0.177)	(0.487)
Emergency ODA (residuals)	0.006*	0.140***	0.018***
	(0.016)	(0.000)	(0.000)
Ideological distance from the US	0.004	-0.171	-0.095*
	(0.675)	(0.293)	(0.025)
Controls:			
Conflict	0.017	-0.019	0.052
	(0.305)	(0.948)	(0.338)
Drought	0.089***	1.091***	0.201**
	(0.000)	(0.001)	(0.003)
Extreme temperature and co-occurring disasters	0.087***	1.074**	0.197**
	(0.000)	(0.004)	(0.008)
Flood	0.007	-0.252	-0.013
	(0.764)	(0.291)	(0.729)
Storm	0.037**	0.245	0.032
	(0.005)	(0.242)	(0.513)
Number of observations	1731	1731	1731
Bayesian Information Criterion	69.279	1193.679	310.849
Log likelihood	21.284	-540.916	-99.501

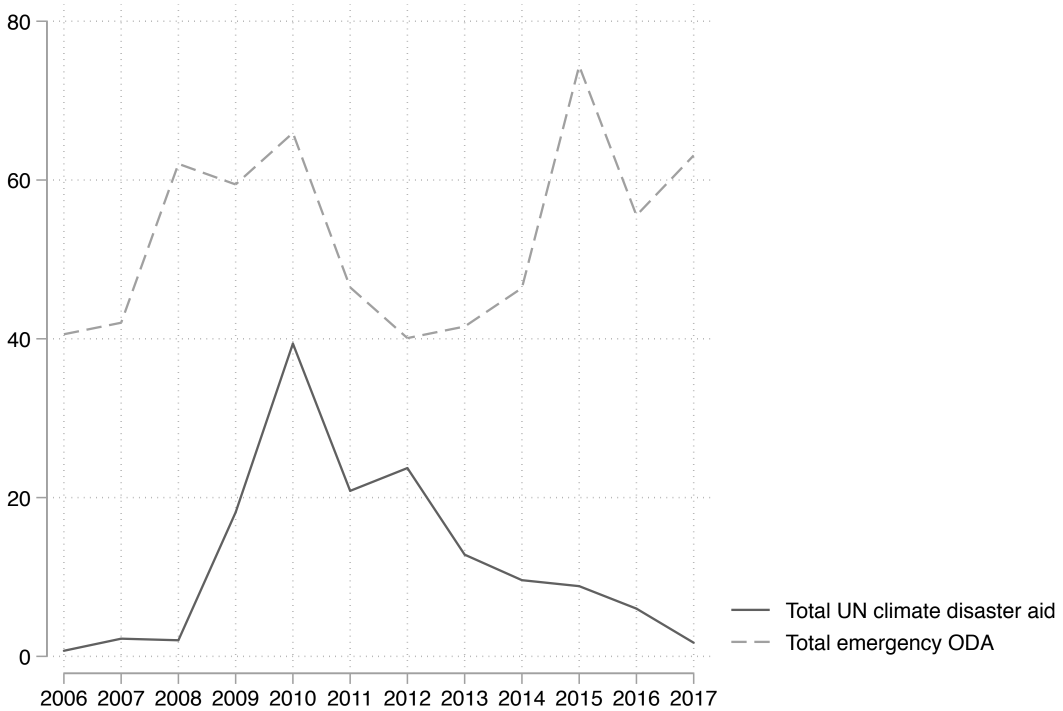

Figure S1. Total UN climate-related disaster aid and emergency ODA in million USD in 2010 prices. UN aid includes CERF, CBPF and other bilateral and multilateral aid coordinated by the UN. Emergency ODA is defined in the official database of the Development Assistance Committee (DAC) of the Organisation for Economic Co-operation and Development (OECD) as including all government aid after natural or humanitarian disasters, including grants, “soft loans”, and technical assistance (30).

The surge in emergency ODA and UN disaster aid between 2008 and 2010 was likely influenced by rising demand for humanitarian assistance in vulnerable countries, reflected in the total number of affected people by climate-related disasters (18). A prominent example is the 2009/2010 drought in Afghanistan which, according to CERF reports, required sustained UN assistance in the areas of agriculture, health, nutrition, water, sanitation, and hygiene over a two-year period. The total number of affected people decreased between 2010 and 2017, with the total number of affected people decreasing by 64 percent in the category of droughts; by 70 percent in the category of floods; by 92 percent in the category of landslides (total affected by extreme temperature and storms remain roughly unchanged) (18).

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