Humanitarian need drives multilateral disaster aid

Lisa M. Dellmuth[a,1], Frida A.-M. Bender[b], Aiden R. Jönsson[b], Elisabeth L. Rosvold[a], and Nina von Uexkull[c]

[a]Department of Economic History and International Relations, Stockholm University, 10691 Stockholm, Sweden; [b]Department of Meteorology and Bolin Centre for Climate Research, Stockholm University, 10691 Stockholm, Sweden; and [c]Department of Peace and Conflict Research, Uppsala University, 75120 Uppsala, Sweden

Edited by Arild Underdal, University of Oslo, Oslo, Norway, and approved December 17, 2020 (received for review August 31, 2020)

As the climate changes, human livelihoods will increasingly be threatened by extreme weather events. To provide adequate disaster relief, states extensively rely on multilateral institutions, in particular the United Nations (UN). However, the determinants of this multilateral disaster aid channeled through the UN are poorly understood. To fill this gap, we examine the determinants of UN disaster aid using a dataset on UN aid covering almost 2,000 climate-related disasters occurring between 2006 and 2017. We make two principal contributions. First, we add to research on disaster impacts by linking existing disaster data from the Emergency Events Database (EM-DAT) to a meteorological reanalysis. We generate a uniquely global hazard severity measure that is comparable across different climate-related disaster types, and assess and bolster measurement validity of EM-DAT climate-related disasters. Second, by combining these data with social data on aid and its correlates, we contribute to the literature on aid disbursements. We show that UN disaster aid is primarily shaped by humanitarian considerations, rather than by strategic donor interests. These results are supported by a series of regression and out-of-sample prediction analyses and appear consistent with the view that multilateral institutions are able to shield aid allocation decisions from particular state interests to ensure that aid is motivated by need.

extreme events | disaster relief aid | multilateral institutions | natural hazards | United Nations

Climate change and extreme weather events have been growing concerns over the past decade (1). Future changes in the climate are expected to lead to changes in the frequency, intensity, and duration of extreme events such as heat waves, heavy rain, drought and associated wildfires, and coastal flooding (2). Both the developed and the developing world are affected, but the burden is not shared equally. Since the 1970s, over 95% of deaths from climate- and weather-related disasters have occurred in developing countries (3). Particularly for developing countries, it is a concern that higher frequencies of natural hazards in a warming climate increase the risk of population displacement, social unrest, and conflict (4, 5).

The borderless nature of climate change and the more intense and frequent events expected in the coming decades make addressing climate-related disasters an urgent international policy challenge (4). Recent history has seen multilateral institutions like the United Nations (UN) acquire substantially enlarged authority on the premise that transboundary policy challenges require expanded international cooperation (6). In the area of disaster relief, the UN raises and coordinates relief aid to address immediate needs in stricken areas, providing food, shelter, medical supplies, rescue management, and water security. Against the background of lively debates on UN reforms to make the institution more effective (7), the UN's disaster relief work has seen deep reform in the mid-2000s. Specifically, the emergency relief funds coordinated by the UN Office for the Coordination of Humanitarian Affairs (OCHA) have been endowed with significantly greater financial resources and more flexibility (8).

Multilateral institutions like the UN are built on liberal assumptions to promote international cooperation and help states to overcome collective action problems (9). This leads us to expect that OCHA officials seek to protect aid distribution from the influence of specific donor states' interests to ensure that aid is allocated on the grounds of hazard severity and humanitarian need. However, we know little about the determinants of UN aid. The political economy literature on foreign aid is bifurcated in two large strands of research, one focusing on aid effectiveness (10, 11) and one on aid disbursements; our study fits squarely in the latter tradition. In this tradition, a sizable body of work on multilateral development aid provides ample evidence of donor influence on aid allocations in the Asian Development Bank (12, 13), International Monetary Fund (IMF) (14, 15), and World Bank (16, 17). However, these studies typically do not examine disaster aid. Moreover, a large number of studies on humanitarian aid show influence of strategic donor interests (18–23), but the bulk of these studies focus on bilateral aid in the aftermath of emergencies and not multilateral aid. Taken together, few notable contributions have studied multilateral disaster aid (24–26), implying that we still know little about whether the UN is able to shield itself from strategic donor interests and allocate aid on the basis of humanitarian principles.

In this study, we therefore examine the determinants of UN disaster aid, making a twofold contribution. First, we add to research on disaster impacts by validating geocoded climate-related disasters included in the most comprehensive disaster database existing, Emergency Events Database (EM-DAT) (27, 28), using a meteorological reanalysis, ERA-Interim (29). By validity we refer broadly to construct or measurement validity (30), focusing on whether the common assumption that EM-DAT captures the meteorological extremes of the climatic

Significance

Threats to human livelihoods resulting from natural hazards are increasing due to climate change. Climate-related disasters such as floods, storms, and droughts have destroyed shelter, reduced crop yields, harmed livestock, and fueled conflict, especially in developing countries. The key finding is that UN aid in the aftermath of climate-related disasters is largely driven by humanitarian need. The UN seems able to fend off donor states' strategic interest and allocate more aid after disasters where hazard severity is greater and need is more pressing. Based on this finding, we argue that the UN lives up to its stated principles of neutrality, impartiality, and independence in disaster aid, corroborating the legitimacy of the UN in allocating disaster aid.

Author contributions: L.M.D. and F.A.-M.B. designed research; L.M.D., F.A.-M.B., A.R.J., E.L.R., and N.v.U. performed research; L.M.D., F.A.-M.B., A.R.J., E.L.R., and N.v.U. analyzed data; and L.M.D., F.A.-M.B., A.R.J., E.L.R., and N.v.U. wrote the paper.

The authors declare no competing interest.

This article is a PNAS Direct Submission.

[1]To whom correspondence may be addressed. Email: lisa.dellmuth@su.se.

This article contains supporting information online at https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2018293118/-/DCSupplemental.

Published January 21, 2021.

distribution of related meteorological variables holds. Using this spatially and temporally coherent reconstruction of atmospheric conditions from a forecast model assimilated with observational data, we create hazard severity measures that are comparable across a number of important disaster types: droughts and floods based on precipitation, heat waves and cold waves based on temperature, and storms based on wind speed. Previous literature uses hazard severity measures for specific disaster types separately, such as droughts (31, 32), rainfall shocks, and storms (33).

Second, we advance on previous aid disbursement literature. We include these hazard severity data into a dataset for almost 2,000 disasters from 2006 to 2017 including indicators for aid, humanitarian need, and donor state interests to examine the determinants of UN aid via regression analysis. We consider regression analysis to be a method suitable for investigating the observable implications of our causal assumptions. The method allows us to assign statistical significance at $P < 0.05$ to the relations between aid and its potential driving factors, however, the estimates of effect size remain imprecise. We run a large number of robustness checks, among them a series of out-of-sample prediction analyses, which underpin our main conclusions (*Materials and Methods*).

Results

We present the results in two steps, beginning with the creation of the hazard severity measure for climate-related disasters, and then summarizing the results from the regression analysis of UN aid.

EM-DAT Validation. Estimating the physical and social determinants of UN aid requires a measure of natural hazard severity for several types of disasters. For this purpose, we first validate whether the disasters reported in EM-DAT correspond to meteorological extremes and, as a second step, estimate their severity at the yearly and country level (see *SI Appendix*, *Text* for details).

As a first step, to match geocoded EM-DAT data to ERA-Interim reanalysis, we rely on daily maximum and minimum temperature for heat waves and cold waves, respectively; accumulated precipitation for floods and droughts; and daily maximum sustained wind speed for storms. This gives us data for droughts, floods, extreme temperature, storms, as well as for disasters where one of these were co-occurring.

Fig. 1 shows distributions of temperature, precipitation, and wind, comparing the EM-DAT–listed disasters, extracted from the gridded reanalysis data using the reported dates and affected geographical regions, to the global reanalysis data during the reference period (2006–2017).

While EM-DAT disaster data have been criticized to suffer from underreporting of damages and missing smaller disasters in low-capacity countries (34), our results are evidence of the validity of the disaster data in the sense that they on average capture a subset of more extreme meteorological events from the total distribution of events. Comparing the means of the control distributions and those representing EM-DAT disasters using Welch's *t* test, results suggest that the disaster event distributions display 1) higher maximum daily wind speed for reported storms, 2) higher daily precipitation for reported floods, 3) lower 180-d accumulated precipitation for reported droughts, 4) higher daily maximum temperature for reported heat waves, and 5) lower daily minimum temperature for reported cold waves.

Daily precipitation was found to better represent extreme conditions for floods, and 180-d accumulated precipitation was found to better represent extreme conditions for droughts. The distributions in Fig. 1, as well as those used for the *t* tests and reported values, are the entire, global distributions (excluding all-ocean cells and latitudes south of 60° S) from ERA-Interim during the time period covered by the geocoded disaster data (2006–2017); randomly sampling subsets of the entire distribution to reduce sample size for the *t* tests does not change the significance of the outcomes. Taken together, this increases our confidence in the EM-DAT database.

As a second step, we use the meteorological data to calculate yearly measures of hazard severity (Table 1). Toward this end, an analysis of meteorological severity is carried out using comparisons of distributions of values and their frequency of occurrence, rather than using the absolute magnitudes of local extremes, as the latter may not be accurately represented in the given record. This method is analogous to the risk-based approach commonly employed in the field of attribution studies, in which climatological extremes in a simulated climate forced with emissions are compared to reference simulations in order to estimate and communicate risks of extreme weather associated with global warming (35). Extremes are then defined and interpreted in the context of a parameter value's place in the overall distribution of values of that parameter and are thus standardized and comparable (*SI Appendix*, *Text*). Climatological distributions of precipitation are used in identifying and studying drought conditions through the use of the Standardized Precipitation Index (SPI) (36), which is also suitable for studying flooding conditions (37). Here, we use the SPI, which is the precipitation expressed in terms of SDs, for flood and drought severity. We use an equivalent approach with wind speed for storms and temperature for heat waves and cold waves.

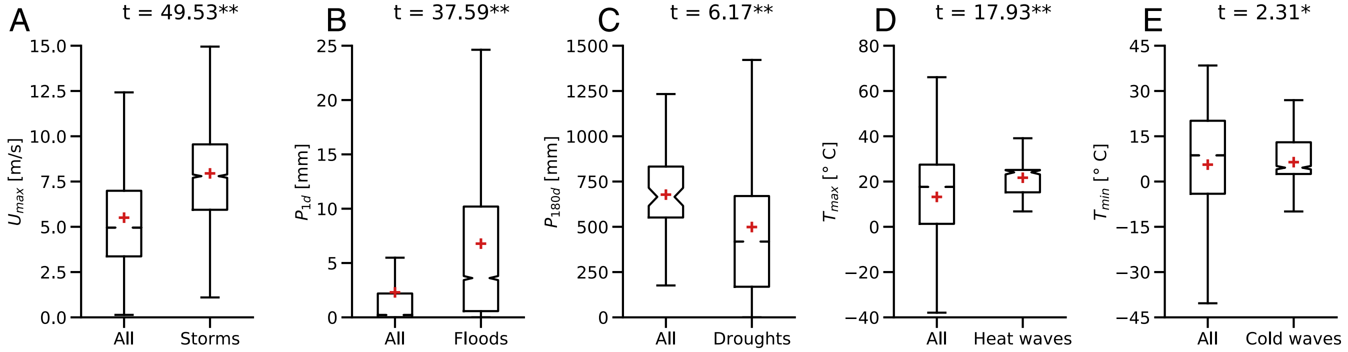

Fig. 1. Overall distributions ("All") compared against EM-DAT–listed disaster distributions of maximum sustained wind speed at 10 m height (U_{max}) during storms (*A*), daily precipitation (P_{1d}) during flooding events (*B*), 180-d accumulated precipitation (P_{180d}) during droughts (*C*), daily maximum temperature at 2-m height (T_{max}) during heat waves (*D*), and daily minimum temperature at 2-m height (T_{min}) during cold waves (*E*). Results of Welch's *t* tests are included (*t*-statistic); $^{*}P < 0.05$, $^{**}P < 0.01$. Red crosses indicate mean values, notches indicate median values, and whiskers indicate quartiles.

Table 1. Meteorological variables used in the calculation of yearly hazard severity

Disaster type		Meteorological variable/index	Yearly hazard severity
Flood	SPI_{1d}	One-day SPI (from dailyaccumulated precipitation)	$\frac{1}{m}\cdot\sum_{i=1}^{n}[SPI_{1d}(i) > +2.0]$
Drought	SPI_{6m}	Six-month SPI (from 180-daccumulated precipitation)	$\frac{1}{m}\cdot\sum_{i=1}^{n}[SPI_{6m}(i) < -2.0]$
Storm	U_{max}	Daily maximum sustainedwind speed at 10 m	$\frac{1}{m}\cdot\sum_{i=1}^{n}[\Delta U_{max}(i) > +2\sigma]$
Heat wave	T_{max}	Daily maximumtemperature at 2 m	$\frac{1}{m}\cdot\sum_{i=1}^{n}[\Delta T_{max}(i) > +2\sigma]$
Cold wave	T_{min}	Daily minimumtemperature at 2 m	$\frac{1}{m}\cdot\sum_{i=1}^{n}[\Delta T_{min}(i) < -2\sigma]$

For each disaster, the hazard severity measure is calculated as the number of daily events (on day i) per year (with n days) that meet the condition (notated with Iverson brackets; i.e., $[P] = 1$ if the condition P is true, otherwise, $[P] = 0$). Δ represents the variable's deviation from its climatological mean; all deviations and means are calculated for each grid cell's distribution of values, as climate is specific to locality. All values are normalized by the number of data points (ERA-Interim grid cells) m for comparability.

Determinants of UN Climate-Related Disaster Aid. Based on the validation that corroborates our confidence in the EM-DAT database, we match the hazard severity measure to our dataset of UN aid. UN disaster aid is coordinated by OCHA in three distinct funding categories where donor state interests can enter the allocation process in different ways: immediate disaster relief, disaster reconstruction, and other bilateral and multilateral aid. We code one dependent variable for each category.

The first dependent variable captures immediate disaster relief provided by the Central Emergency Response Fund (CERF). Since 2006, countries may request funding through the UN representative in their country in the case of an emergency. The application is assessed and approved by the Emergency Relief Coordinator who is head of OCHA, typically within 48 h. Eligible recipients are UN organizations (excluding OCHA) and the International Organization for Migration. As funds are unearmarked (8), there is very little room for donor interests to influence allocations. CERF assistance amounts to about 0.5 billion US dollars (USD) yearly, of which the share of climate-related disaster aid, as our data shows, fluctuates and makes up half of the yearly funding at the most.

Second, the UN provides disaster reconstruction aid through different Country Based Pooled Funds (CBPF). Through the Consolidated Appeals Process, funds are raised and pooled in a CBPF. Decisions about fund allocations are typically made by local committees involving nongovernmental organizations (NGOs) and a UN Humanitarian Coordinator. An advisory board in which donors, NGOs, and UN agencies are relatively equally represented oversees funding decisions. Funds are unearmarked but target specific countries (38), leaving some room for donor influence by way of channeling funding to select countries. CBPFs amount to slightly less than 1 billion USD a year in total, of which climate-related disaster aid in our dataset amounts to about 75% of total CBPF aid a year.

The third dependent variable includes other bilateral and multilateral aid coordinated by OCHA. According to the records in OCHA's Financial Tracking Service, this type of aid is typically earmarked and more diversified, implying that donors might pursue a broader set of different objectives with these funds than with CERF and CBPF assistance. Our data reveal that yearly disbursements of these funds strongly fluctuate between about 0.5 and 5 billion USD.

These three dependent variables are examined in terms of whether they are associated with a range of needs-related and strategic factors, as well as a number of controls, in a Tobit regression analysis. As the dependent variables are log transformed, the coefficients can be interpreted in terms of a percentage change until an about 20% increase or decrease (*Materials and Methods*).

The key finding is that hazard severity and humanitarian need matter for aid allocations, while there is mixed evidence for strategic donor interests. Hazard severity is found to be positively associated with aid in models 2 and 3, implying that hazard severity is taken into account for longer-term but not for short-term CERF aid allocations. This may be understood against the background of the timing of funding: CBPF and other forms of aid are decided upon in a longer process than CERF aid, and

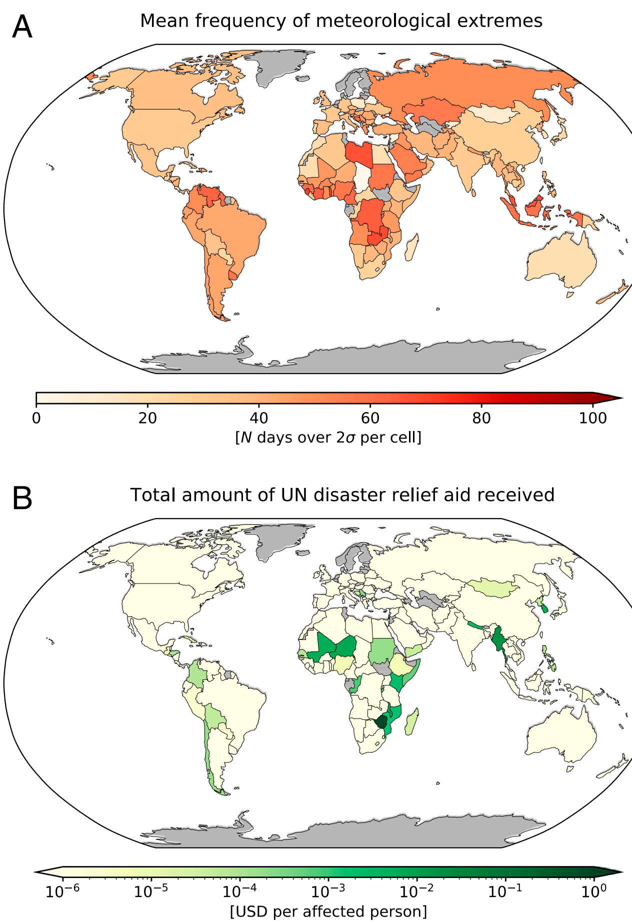

Fig. 2. Hazard severity (*A*) and total UN aid per affected person (*B*), averages for 2013–2017. Total UN aid includes aid including immediate disaster relief (CERF aid), disaster reconstruction aid (CBPF aid), and other bilateral and multilateral aid raised by the UN.

https://doi.org/10.1073/pnas.2018293118

decision-makers may therefore be able to consider a broader knowledge basis, including hazard severity. We illustrate this finding by providing a geographical overview of the hazard severity measure and total UN aid (Fig. 2). The maps illustrate that high hazard severity often, but not always, coincides with UN climate-related disaster aid, such as in the case of Congo, Indonesia, Russia, and Zambia. They also suggest that UN disaster aid mostly flows to Latin America and Subsaharan and eastern Africa.

Moreover, the results suggest that both CERF and CBPF aid are positively associated with the number of affected persons, respectively, but other bilateral and multilateral funding is not. More fragile states appear to receive greater UN aid in all three spending categories. These results are robust across a large number of alternative model specifications (*Materials and Methods*).

Regarding strategic factors, only emergency official development aid (ODA), which includes all government development aid for emergencies, corroborates the donor states' strategic interest argument across the board. This indicates that UN decision-makers partially mimic emergency ODA allocations ("bandwagoning effect") rather than tending to allocate lower funding to areas receiving larger amounts of emergency ODA partially through bilateral sources ("crowding out effect"). Trade openness and status as a former colony of one of the permanent five members of the UN Security Council (UNSC) ("P5") do not appear to matter. The coefficient of oil endowment is negative and significant in model 1, which runs against the expectation of donor influence; rather, this might indicate that oil exporters are less likely to apply for immediate disaster aid, but this effect is not consistent across model specifications (*Materials and Methods*). Similarly, the results for UN General Assembly (UNGA) voting are mixed: They suggest that countries voting in line with the United States (US) in the UNGA tend to receive more CBPF and other bilateral or multilateral aid (models 2 and 3), while the negative effect of UNGA voting on CERF aid is not in line with the strategic influence argument (model 1), and not robust (*Materials and Methods*).

With regard to the control variables, the results suggest that UN aid especially targets droughts, extreme temperature, and co-occurring disasters, and that CERF aid particularly targets storm-related disasters. Ongoing armed conflict in the disaster-struck country does not appear to matter for aid disbursement.

Taken together, the evidence underlines the needs-based argument. Additional out-of-sample cross-validations give further support to the regression results by suggesting that the group of needs-related factors are better predictors of UN aid than the group of strategic factors (*SI Appendix*, Table S20).

Discussion

This study speaks to both aid and disaster impact research. It has examined whether humanitarian need or donor states' interests determine UN disaster aid. Evidence from a series of regression and out-of-sample prediction analyses endorse that needs are more important than strategic interests in determining UN-coordinated disaster aid allocations. This finding aligns with previous studies recognizing the autonomous influence of the bureaucracies of multilateral institutions disbursing humanitarian aid (24–26, 39). It also underpins the insight that US commercial or political interests do not tend to shape US humanitarian aid (19). However, given that the bulk of humanitarian aid (19–23) and multilateral development aid research (12–17) has argued that strategic political alliances or donor states crucially shape aid flows, this study provides a more nuanced view of multilateral aid disbursement.

Indeed, we find only one strategic factor to be consistently related to UN aid. UN aid appears to partly mimic emergency ODA, which mirrors previous findings in the context of humanitarian aid (19, 25). Similarly, NGOs have been shown to mimic state behavior in broader ODA allocations (40, 41). Political economy theories of transaction costs (42) lead us to expect that in light of information asymmetries in disaster aid, donors to some extent use information about existing aid flows as a proxy for the usefulness of aid. This suggests that donors crucially depend on the information exchanged in multilateral institutions such as the UN.

Moreover, countries that tend to vote in line with the United States in the UNGA do not appear to receive more CERF aid, and the evidence for an effect of CBPF and other bilateral and multilateral disaster aid is mixed. This corroborates previous studies that have not found a consistent effect of UNGA voting on humanitarian aid (39) and suggests that UNGA voting matters rather in the context of IMF loans (43). Related, we do not find that countries that rotate onto the UN Security Council receive preferential CERF and CBPF treatment, in contrast to previous works on IMF lending (15), World Bank development aid (44), and UNICEF development aid (45). Together, the results support previous theories attributing legitimate authority to multilateral institutions because they ensure political neutrality, integrity, and protection of the most vulnerable (46).

The second contribution lies in the thorough investigation into the validity of the disaster data on the basis of which the results on climate-related disaster aid are generated. EM-DAT is the most comprehensive dataset on disaster occurrence to exist, but it is known to suffer from biases in disaster severity measurements (47). The results from our validation using reanalysis suggest that EM-DAT disasters indeed represent extreme values in the distributions of corresponding meteorological variables in the ERA-Interim dataset. That we find EM-DAT disasters to capture extreme weather events substantiates the validity of the EM-DAT disaster data.

Moreover, we propose a hazard severity measure that allows for comparing disasters across disaster types, in contrast to previous disaster literature that typically operates with hazard measures for specific types, such as droughts (31, 32) and extreme rainfall (33). Including the hazard severity measure in the regression analysis of UN aid offers an alternative to existing endogenous severity measures often used in disaster research. At the same time, by including only events that we know were disasters (i.e., recorded in EM-DAT), we avoid measuring extreme weather that did not actually impact people. Finally, our proposed hazard severity measure, whose robust effects on UN aid we demonstrated in this article, could enable comparative analyses of the causes and impacts of climate-related disasters across countries, disasters types, and over time.

Materials and Methods

EM-DAT Validation. ERA-Interim (29) is a global gridded reanalysis, i.e., a spatially and temporally coherent reconstruction of atmospheric conditions, from a forecast model assimilated with observational data. Based on meteorological variables in the reanalysis, a variety of disaster types can be identified and characterized: droughts and floods based on precipitation, heat waves and cold waves based on temperature, and storms based on wind speed. We overcome challenges related to the limited spatial resolution of the reanalysis by using the frequency of events with a magnitude beyond a specific threshold of deviations from the mean to quantify hazard severity at annual resolution. The choice of thresholds and time scales, as well as their limitations, are discussed in detail in *SI Appendix*, *Text*. Using shapefiles of the first-order administrative units provided by the Database of Global Administrative Areas (48), the relevant meteorological data are extracted from the reanalysis. The distribution of meteorological conditions during reported disasters in the administrative unit is then compared to the overall distribution of the same variable over the same time period to test the difference between the EM-DAT–defined disaster cases and the reference state.

Materials for UN Aid Regression. The dataset is coded at the level of disasters, which are clustered in disaster types, countries, and years. For the regression analysis, we code a number of different proxies for need and donor interests. We include those that do not raise any multicollinearity concerns in the main

Table 2. Regression analysis of UN aid

	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**
	(0.175)	(0.001)	(0.003)
Total affected persons (log)	0.003**	0.033*	−0.000
	(0.002)	(0.017)	(0.835)
State fragility index	0.002***	0.029***	0.006**
	(0.000)	(0.000)	(0.003)
Strategic factors			
PTAs signed	−0.002	−0.105	−0.014
	(0.776)	(0.392)	(0.678)
Former P5 colony	−0.010	−0.130	0.035
	(0.318)	(0.423)	(0.350)
Oil endowment	−0.009*	−0.092	−0.012
	(0.029)	(0.199)	(0.417)
Emergency ODA (residuals)	0.006*	0.144***	0.018***
	(0.020)	(0.000)	(0.000)
UNGA voting with the United States	−0.072*	2.610***	0.450*
	(0.037)	(0.001)	(0.027)
Controls:			
Conflict	0.017	−0.040	0.061
	(0.310)	(0.894)	(0.244)
Drought	0.090***	1.070***	0.197**
	(0.000)	(0.001)	(0.003)
Extreme temperature and co-occurring disasters	0.088***	1.050**	0.196**
	(0.000)	(0.004)	(0.004)
Flood	0.006	−0.248	−0.013
	(0.797)	(0.292)	(0.725)
Storm	0.037**	0.224	0.035
	(0.006)	(0.281)	(0.525)
No. of observations	1,731	1,731	1,731
Bayesian Information Criterion	62.026	1,161.896	304.797
Log likelihood	24.910	−525.025	−96.475

Constant included but not reported. *P* values in parentheses, estimated on the basis of heteroscedasticity-robust (Huber–White) SEs, clustered at the level of years. $^*P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$. Estimates from a Tobit regression model. See *Materials and Methods* for model specification. Preferential trade agreements abbreviated as PTA.

analysis in Table 2 and use the other measures for robustness checks (see below). All variables that are described in detail in *SI Appendix*, *Text* and Tables S1–S3 provide sources, descriptive statistics, and correlations between the variables.

In the selection of variables, we are guided by the commonly applied disaster risk framework in which risk is seen as the product of hazard, exposure, and vulnerability (1, 39, 49). Our measures used to operationalize the needs argument capture these factors to varying degrees. At the level of disasters, we create a hazard severity measure for each disaster as the sum of daily events in a specific disaster category occurring within a given country and year exceeding two SDs from its climatological mean, normalized by the number of grid cells from which the reanalysis data were taken (Table 1). Humanitarian need is captured by the number of affected people, logarithmized in order to avoid that outliers skew the results, derived from EM-DAT for each disaster (21). At the country level, we account for state fragility as a measure of vulnerability (50).

To measure strategic interests, we include common country-level factors in aid research: the number of preferential trade agreements presigned by recipient state in a given year, as exports to donor countries might incentivize more aid to stabilize the exporting country (22); a dummy variable indicating former colony status of the P5 in the UNSC (=1) (39); a variable capturing the part of emergency ODA left unexplained by the variables included in our model, thereby avoiding multicollinearity and endogeneity (refs. 21 and 40; see *SI Appendix*, *Text*); and an index of voting similarity between a recipient country and the United States in the UNGA in a given year, as the United States is the main OCHA donor (51).

Moreover, we control for intrastate conflict, which enables us to capture the presence of internal challengers and, thus, recipient governments' motivations to apply for or reject offered aid. Governments facing internal challengers could have incentives to refuse international aid in order not to appear weak vis-à-vis internal challengers. An example of this dynamic is the refusal of the government of Myanmar to accept foreign aid following the cyclone Nargis in 2008 (52, 53). We measure the involvement of the government in armed conflict at the country level as a dummy variable indicating 1 if a country experiences at least one ongoing intrastate armed conflict involving the government and resulting in 25 battle-related deaths, and 0 otherwise (54).

Finally, we control for disaster type using a number of dummy coded variables that equal 1 for a specific type of disaster and 0 otherwise (25).

Methods. As about 90% of all disasters during the observed time period did not receive any UN aid and, thus, score zero, the regression analysis uses the Tobit estimator that is appropriate for censored data. Thus, we estimate a cross-sectional model (39). The reason is that disaster year-level aid flows are rather volatile from 1 year to the other (*SI Appendix*, Fig. S1). In contrast, independent variables at the country-year level are slow moving, a known issue in aid research (55). Thus, our main models in Table 2 are based on the assumption that the independent variables are able to explain mean differences in UN funding between disasters, which is why we prefer to use a cross-sectional Tobit estimator with fixed effects for disaster types over a time-series cross-section model. Our analyses use inflation-adjusted measures of UN aid as dependent variables, as we do not include year fixed effects.

The model takes the following generic form: $y_i = max0, x_i\beta + \varepsilon_i$, where $\varepsilon_i \mid x_i$ *Normal* $(0,\sigma^2)$. y_i denotes UN aid for each disaster *i, x* refers to a vector of independent variables, and ε refers to a normally distributed error term, clustered at the level of countries. As the Tobit model has two dependent variables (the censored and the uncensored part), the coefficients do not represent the first-order partial derivative of the covariate, but the marginal effect of the covariates on the latent dependent variable $E(y_i \mid x_i)$, calculated at the mean of the covariates. A test for potential multicollinearity (mean variance inflation factor≈2), and Pearson correlation coefficients indicate no such concern (*SI Appendix*, Table S3).

Robustness Checks. The results are robust across a large number of model specifications. First, we control for country-level indicators of government capacity, such as gross domestic product (GDP) (ref. 26, *SI Appendix*, Table S4), export orientation in terms of trade in percent of GDP (ref. 2, *SI Appendix*, Table S5), infant mortality (ref. 39, *SI Appendix*, Table S6), and corruption (ref. 22, *SI Appendix*, Table S7). We also control for logarithmized disaster-level population density (refs. 21 and 26; *SI Appendix*, Table S8). Due to multicollinearity, these specifications are less efficient, but our results remain robust except that oil endowment and UNGA voting aligning with the United States become insignificant in model 1 when controlling for GDP and corruption. The additional variables themselves show no effects except for GDP and corruption in model 1, suggesting that CERF aid flows to poorer and less corrupt countries.

Second, we suspect that the total number of affected people might be more strongly associated with UN aid at higher levels of hazard severity, which we operationalize by a product term between affected people and hazard severity (*SI Appendix*, Table S9). However, we find no evidence for an interaction.

Third, we test the robustness of the strategic variables. For the sake of a more conservative test, we enter all strategic variables separately in the models. The results remain robust (*SI Appendix*, Tables S10–S12). Moreover, we tested a number of additional strategic variables common in aid research (15, 22, 40): temporary UNSC membership (*SI Appendix*, Table S13), being a recipient of IMF assistance (*SI Appendix*, Table S14), and a dummy variable indicating if a recipient country was subject to US sanctions in a given year (=1) (*SI Appendix*, Table S15). We find no effects, and the results are robust.

Fourth, we model time in different ways. To do so, we test if a potential trend in aid flows might bias the results (*SI Appendix*, Fig. S1). Including a count variable coded as a consecutive number increasing each year over the time period covered yields no consistent evidence for an effect of a trend, but again, the UNGA voting variable turns insignificant in model 1 (*SI Appendix*, Table S16). We also reran the models as logistic models with binary dependent variables (=1 if a country received UN aid). We run these models both as cross-sectional logit regression (*SI Appendix*, Table S17) and time-series cross-sectional logit regression with country-fixed effects (*SI Appendix*, Table S18). The results corroborate the preferred Tobit model specification, as they leave our main conclusions unchanged. In fact, the coefficient of hazard severity turns significant in model 1 (*SI Appendix*, Tables S17 and S18), and the coefficient of UNGA voting becomes insignificant (*SI Appendix*, Table S18), which further corroborates our main conclusion.

Fifth, we address potential endogeneity issues arising from joint determination of the dependent and one or several independent variables (simultaneity). While omitted variable bias is generally not a problem in foreign aid research, endogeneity due to simultaneity often is. For example, aid and disaster reporting may be simultaneously a function of state capacity. Given the general absence of aid effects on institutions and short-term economic outcomes, these are negligible concerns. We rule out instrumenting as an appropriate option, which typically yields less precise estimations (55), and prefer to test if endogeneity might compromise the results in the two following ways.

The first way is to lag country-level indicators by 1 y, which yields consistent results (*SI Appendix*, Table S19). The second is to conduct an out-of-sample cross-validation that estimates the contribution of the different groups of explanatory factors. It ascertains whether the group of needs-based variables or the group of strategic variables, or both combined, fare better at predicting UN aid out of sample. Similar to regression modeling, this prediction approach serves to test observable implications of relevant theories (56). Endogeneity concerns do not arise as the focus is on the predictive power of groups of variables. We find that across dependent variables, the "needs model" predicts better out of sample than the "strategic model." While the combined model including all variables performs best, the improvement over the more parsimonious model only including needs-based variables is small, indicating that adding strategic factors leads only to slight improvements for predicting UN aid (*SI Appendix*, Table S20).

Finally, given that the coefficients of UNGA voting are not robust in the model specifications above, we use an alternative indicator for ideological closeness to the United States in the UNGA. We enter it separately, as it is highly correlated with UNGA voting ($r = -0.627$; $n = 1{,}791$). The results are mixed, indicating that countries with greater ideological distance to the United States receive less other bilateral and multilateral aid, but there is no association with CERF and CBPF aid (*SI Appendix*, Table S21).

Data Availability. Quantitative data have been deposited in Harvard Dataverse (https://doi.org/10.7910/DVN/VWQ5AY) (57).

ACKNOWLEDGMENTS. We thank Margareta Wahlström and the participants of the Joint Uppsala University-Peace Research Institute Oslo (PRIO) Workshop on Climate Change and Security in September 2018, and the "Glocalizing Climate Governance (GlocalClim)" project workshop in January 2020, for insightful comments. Agnese Loy and Christian Hultgren provided excellent research assistance. The computations for the meteorological analyses were performed on resources provided by the Swedish National Infrastructure for Computing at the National Supercomputing Centre. Finally, financial support from Bolin Centre and the Board of Environmental Research members in the Human Sciences at Stockholm University, "Mistra Geopolitics—Navigating towards a Secure and Sustainable Future" Grant 2016/11#5, "Glocalizing Climate Governance (GlocalClim)" funded by Formas Grant 2018-01705, as well as "Climate Change, Food Insecurity and Violent Conflict" (Swedish Research Council, Swedish International Development Cooperation Agency (SIDA), and Formas, Grant 2016-06389) is gratefully acknowledged.

1. Intergovernmental Panel on Climate Change (IPCC), "Summary for policymakers" in *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change*, C.B. Field, Ed. *et al*. (Cambridge University Press, Cambridge, UK and New York, NY, 2012), pp. 1–19.
2. Intergovernmental Panel on Climate Change (IPCC), "Summary for policymakers" in *Global Warming of 1.5°C. An IPCC Special Report on the Impacts of Global Warming of 1.5°C above Pre-Industrial Levels and Related Global Greenhouse Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Change, Sustainable Development, and Efforts to Eradicate Poverty*, V. Masson-Delmotte, Ed. *et al*. (World Meteorological Organization, Geneva, Switzerland, 2018), pp. 3–24.
3. J. Handmer *et al*., "Changes in impacts of climate extremes: human systems and ecosystems" in *Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation - A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC)*, C.B. Field *et al*., Eds. (Cambridge University Press, Cambridge, UK, 2012), pp. 231–290.
4. M. Brzoska, Understanding the disaster-migration-violent conflict nexus in a warming world: The importance of international policy interventions. *Soc. Sci.* **8**, 1–17 (2019).
5. V. Koubi, T. Böhmelt, G. Spilker, L. Schaffer, The determinants of environmental migrants' conflict perception. *Int. Organ.* **72**, 905–936 (2018).
6. L. Hooghe *et al*., *Measuring International Authority: A Postfunctionalist Theory of Governance* (Oxford University Press, Oxford, UK, 2017), vol. III.
7. T. G. Weiss, *What's Wrong with the United Nations and How to Fix it* (Polity, Cambridge, UK, 2012).
8. T. D. Robinson, T. M. Oliveira, S. Kayden, Factors affecting the United Nations' response to natural disasters: What determines the allocation of the central emergency response fund? *Disasters* **41**, 631–648 (2017).
9. R. O. Keohane, D. G. Victor, Cooperation and discord in global climate policy. *Nat. Clim. Chang.* **6**, 570–575 (2016).
10. C. Burnside, D. Dollar, Aid, policies and growth. *Am. Econ. Rev.* **90**, 847–868 (2000).
11. World Bank, *Assessing Aid: What Works, What Doesn't, and Why* (Oxford University Press, Oxford, UK, 1998).
12. C. Kilby, Donor influence in multilateral development banks: The case of the Asian development bank. *Rev. Int. Organ.* **1**, 173–195 (2006).
13. D. Lim, J. Vreeland, Regional organizations and international politics: Japanese influence over the Asian development bank and the UN security council. *World Polit.* **65**, 34–72 (2013).
14. M. S. Copelovitch, Master or servant? Common agency and the political economy of IMF lending. *Int. Stud. Q.* **54**, 49–77 (2010).
15. A. Dreher, J. E. Sturm, J. R. Vreeland, Global horse trading: IMF loans for votes in the United Nations security council. *Eur. Econ. Rev.* **53**, 742–757 (2009).
16. E.L. Rosvold, Disaggregated determinants of aid: Development aid projects in the Philippines. *Dev. Policy Rev.*, 10.1111/dpr.12465 (2020).
17. G. Zhang, The determinants of foreign aid allocation across China: The case of World Bank loans. *Asian Surv.* **44**, 691–710 (2004).
18. O. Becerra, E. Cavallo, I. Noy, Foreign aid in the aftermath of large natural disasters. *Rev. Dev. Econ.* **18**, 445–460 (2014).
19. C. Bommer, A. Dreher, M. Perez-Alvarez, Home bias in humanitarian aid: The role of regional favoritism in the allocation of international disaster relief. *CEPR Discussion Paper 13957* (2019).

20. A. C. Drury, R. S. Olson, D. A. van Belle, The politics of humanitarian aid: U.S. Foreign disaster assistance, 1964–1995. *J. Polit.* **67**, 454–473 (2005).
21. G. Fink, S. Redaelli, Determinants of international emergency aid. Humanitarian need only? *World Dev.* **39**, 741–757 (2011).
22. A. Fuchs, N.-H. Klann, "Emergency aid 2.0." (Beiträge zur Jahrestagung des Vereins für Socialpolitik 2013: Wettbewerbspolitik und Regulierung in einer globalen Wirtschaftsordnung—Session: International Trade and Finance No. D08-V3, 2013).
23. G. R. Olsen, N. Carstensen, K. Høyen, Humanitarian crises: What determines the level of emergency assistance? Media coverage, donor interests and the aid business. *Disasters* **27**, 109–126 (2003).
24. V. Eichenauer, A. Fuchs, S. Kunze, E. Strobl, Distortions in aid allocation of United Nations flash appeals: Evidence from the 2015 Nepal earthquake. *World Dev.* **136**, 105023 (2020).
25. D. Fielding, The dynamics of humanitarian aid decisions. *Oxf. Bull. Econ. Stat.* **76**, 536–564 (2014).
26. P. A. Raschky, M. Schwindt, On the channel and type of aid: The case of international disaster assistance. *Eur. J. Polit. Econ.* **28**, 119–131 (2012).
27. D. Guha-Sapir, R. Below, P. Hoyois, "EM-DAT: International disaster database. Brussels: Centre for research on the Epidemiology of disasters (CRED)." Université Catholique de Louvain. https://www.emdat.be. Accessed 5 May 2020.
28. E.L. Rosvold, H. Buhaug, Geocoded Disasters (GDIS) Dataset, 1960-2018 (Preliminary Release). (NASA Socioeconomic Data and Applications Center [SEDAC], Palisades, NY). https://doi.org/10.7927/zz3b-8y61. Accessed 18 November 2020.
29. D. P. Dee *et al*., The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Q. J. R. Meteorol. Soc.* **137**, 553–597 (2011).
30. R. Adcock, D. Collier, Measurement validity: A shared standard for qualitative and quantitative research. *Am. Polit. Sci. Rev.* **95**, 529–546 (2001).
31. S. A. Rustad, E. L. Rosvold, H. Buhaug, Development aid, drought, and coping capacity. *J. Dev. Stud.* **56**, 1578–1593 (2019).
32. N. von Uexkull, M. Croicu, H. Fjelde, H. Buhaug, Civil conflict sensitivity to growing-season drought. *Proc. Natl. Acad. Sci. U.S.A.* **113**, 12391–12396 (2016).
33. J. Eastin, Hell and high water: Precipitation shocks and conflict violence in the Philippines. *Polit. Geogr.* **63**, 116–134 (2018).
34. S. Acevedo, Gone with the Wind: Estimating hurricane and climate change costs in the Caribbean. *IMF Working Paper* WP/16/199 (2016).
35. F. E. Otto, Attribution of weather and climate events. *Annu. Rev. Environ. Resour.* **42**, 627–646 (2017).
36. T. B. McKee, N. J. Doesken, J. Kleist, "The relationship of drought frequency and duration to time scales" in *Proceedings of the Eighth Conference on Applied Climatology* (American Meteorological Society, Boston, MA, 1993), pp. 179–184.
37. R. A. Seiler, M. Hayes, L. Bressan, Using the standardized precipitation index for flood risk monitoring. *Int. J. Climatol.* **22**, 1365–1376 (2002).
38. United Nations Office for the Coordination of Humanitarian Affairs, "Operational Handbook for Country-based Pooled Funds, Version 1.2." https://www.unocha.org/our-work/humanitarian-financing/country-based-pooled-funds-cbpf/cbpf-guidelines. Accessed 28 November 2020.
39. N. Narang, Forgotten conflicts: Need versus political priority in the allocation of humanitarian aid across conflict areas. *Int. Interact.* **42**, 189–216 (2016).
40. A. Dreher, P. Nunnenkamp, H. Öhler, J. Weisser, Acting autonomously or mimicking the state and peers? A panel Tobit analysis of financial dependence and aid allocation by Swiss NGOs. *KOF Working Paper No. 219* (2009). 10.2139/ssrn.1362437.
41. A. Fuchs, H. Öhler, Does private aid follow the flag? An empirical analysis of humanitarian assistance. *World Econ.*, 1–35, 10.1111/twec.13021 (2020).
42. M. J. Gilligan, "The transaction costs approach to international institutions" in *Power, Interdependence, and Nonstate Actors in World Politics*, H. Milner, A. Moravcsik, Eds. (Princeton University Press, Princeton, NJ, 2009), pp. 51–65.
43. R. W. Stone, The political economy of IMF lending in Africa. *Am. Polit. Sci. Rev.* **98**, 577–591 (2004).
44. C. Kilby, The political economy of project preparation: An empirical analysis of World Bank projects. *J. Dev. Econ.* **105**, 211–225 (2013).
45. I. Kuziemko, E. Werker, How much is a seat on the security council worth? Foreign aid and bribery at the United Nations. *J. Polit. Econ.* **114**, 905–930 (2006).
46. A. Buchanan, R. O. Keohane, The legitimacy of global governance institutions. *Ethics Int. Aff.* **20**, 405–437 (2006).
47. R. Slettebak, Don't blame the weather! climate-related natural disasters and civil conflict. *J. Peace Res.* **49**, 163–176 (2012).
48. GADM, "Database of Global Administrative Areas, Version 3.6." gadm.org/index.html. Accessed 6 May 2020.
49. M. Oppenheimer *et al*., "Emergent risks and key vulnerabilities" in *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel of Climate Change*, C. B. Field *et al*., Eds. (Cambridge University Press, Cambridge, UK, 2014), pp. 1039–1099.
50. A. Eriksson, Y. K. Ohlsén, R. Garfield, J. von Schreeb, Who is worst off? Developing a severity-scoring model of complex emergency affected countries in order to ensure needs based funding. *PLoS Curr.* **7**, ecurrents.dis.8e7fb95c7df19c5a9ba56584d6aa2c59 (2015).
51. M. A. Bailey, A. Strezhnev, E. Voeten, Estimating dynamic state preferences from United Nations voting data. *J. Conflict Resolut.* **61**, 430–456 (2017).
52. P. Wooyeal, Authoritarianism and humanitarian aid: Regime stability and external relief in China and Myanmar. *Pac. Rev.* **24**, 439–462 (2011).
53. T. Nelson, Rejecting the gift horse: International politics of disaster aid refusal. *Conflict Secur. Dev.* **10**, 379–402 (2010).
54. T. Pettersson, S. Högbladh, M. Öberg, Organized violence, 1989–2018 and peace agreements. *J. Peace Res.* **56**, 589–603 (2019).
55. A. Dreher, F. Mölders, P. Nunnenkamp, Aid delivery through non-governmental organisations: Does the aid channel matter for the targeting of Swedish aid? *World Econ.* **33**, 147–176 (2010).
56. B. A. Desmarais, What can we learn from predictive modeling? *Polit. Anal.* **25**, 145–166 (2017).
57. L. Dellmuth, F. A.-M. Bender, A. R. Jönsson, E. L. Rosvold, N. von Uexkull, Replication data for: Humanitarian need drives multilateral disaster aid. *Harvard Dataverse*, V1. https://doi.org/10.7910/DVN/VWQ5AY. Deposited 8 January 2021.