Beg or bargain? The impact of disastrous extreme weather events on foreign aid delivery*

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Abstract

How do exogenous shocks impact the bargaining process between foreign aid providers and recipients? This paper investigates the dynamic effects of a country's exposure to climate-related disasters on foreign aid delivery mechanisms. I use provider-recipient dyadic data between the major providers and recipient countries over 15 year (2005-2015), disaggregated by state and nonstate channels. I leverage unstructured information on the name of the primary implementing partner reported to the OECD to impute missing data on projects' delivery mechanism. I also combine geospatial information on disasters and grid-level weather data to build a physical measure of hazard intensity. For the identification of dynamic effects, I follow a multiple event study approach that allows for non-binary treatments to switch on and off, and treatment lags to affect the outcome. Focusing on the recipient perspective, results show that the effect of extreme weather events on aid delivery mechanisms depends on the interaction between international and domestic political factors that determine the recipient government's agency.

Introduction

Between 1970 and 2019, more than 11 000 disasters were attributed to weather, climate and water-related hazards. Catastrophic events such as floods, droughts, storms or heatwaves accounted for over 2 million deaths and US$ 3.64 trillion in losses (Douris and Geunhye 2021). Population and material growths have increased the exposure to extreme events and their socioeconomic damages. Besides, climate change will continue increasing the frequency and intensity of extreme events (IPCC 2023). Extreme weather and climate events have impacts both within and between countries. Cross-country negative spillovers create incentives to provide external assistance for both donors pursuing their strategic

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interests and others aiming for poverty alleviation (Bermeo 2017). It can create "windows of opportunities" for foreign influence on domestic issues (Cheng and Minhas 2021) and it is more effective in countries that are more vulnerable to external shocks, due to its cushioning effect (Chauvet and Guillaumont 2009).

However, disasters are more likely in weak institutional environments where aid is less effective and the risk of aid capture higher. Aid – like natural resource revenues – can encourage rent seeking and undermine governmental accountability to its own citizens, by reducing its dependence on domestic taxpayers for revenues (Bueno de Mesquita and Smith 2009). It can even be detrimental to the political stability of the recipient country if local sociopolitical dynamics are not sufficiently taken into account (Findley 2018).

In response to challenges related to working directly with state institutions, donors use the composition and modalities of aid strategically Dietrich (2021). They adapt their aid distribution to determine the degree of delegation of authority given to the recipient government Dreher, Langlotz, and Marchesi (2017) and how much they are willing to invest in country systems (Knack 2013).

One important instrument to determine control over aid is the channel of delivery. Donors can provide aid either through State channels or non-state channels. State channels involve direct transfers to the recipient's public institutions and lead to higher delegation of authority on how aid will be disbursed. Non-State channels include indirect deliveries through official or private actors, such as UN agencies, non-governmental organizations (NGOs), or private companies.

Bypassing local state institutions to implement aid activities through nonstate actors can increase aid effectiveness Usmani, Jeuland, and Pattanayak (2022) and empower civil society in autocratic regimes (DiLorenzo 2018). However, it can also undermine the state legitimacy and accountability in the provision of public services Deserranno, Nansamba, and Qian (2025). Besides, donors have less leverage to support friendly regimes or to buy policy concessions through bypass aid (Allen, Ferry, and Shammama 2024).

The delegation of authority on aid implementation by an aid agency to a recipient government results from a bargaining process in an uncertain environment (Swedlund 2017). Both actors weight the costs and benefits between the amount and the composition of the aid package Dietrich (2013). Due to cross-border interdependences, external shocks create incentives for the aid agency to delegate authority to the local authorities in order to mitigate impacts. However, information asymmetry and agency bias create incentives to keep control over the funds and bypass country systems.

Most of the literature on the aid bargaining process adopts a donor perspective. Here, I consider the recipient perspective. Recipients' agency in negotiations is important to consider because donors have to get the approval of state authorities before intervening in a country. It also reflects the enduring call for ownership over foreign aid conveyed by the 2005 Paris Declaration on Aid Effectiveness.

I use a principal-agent framework to look at the recipient government's policy choice, building on previous work by Annen and Knack (2021) and showing how its links with other models by Bourguignon and Gunning (2020) and Aidt, Albornoz, and Hauk (2021) for instance. Similarly to a two-level bargain game, the recipient government negotiates at the international level with the aid agency for additional resources and the degree of control over them, as well as at the domestic level with its own population for the redistribution of government resources. At the international level, the recipient government faces a trade-off between additional resources and a loss of control (due to higher foreign influence) over available resources. At the domestic level, the government weights the opportunity cost of additional resources allocated to the public good rather than to the private good, that benefits only its supporters, for her political survival. This creates a relationship between the international and domestic political factors. I incorporate an exogenous shock into the model, caused by a climate-related disaster, by assuming that it affects the provision of public good in the recipient country. I show that the government's policy choice relies on available resources besides foreign aid, the preference alignment with the aid agency and on the domestic state-society relationship.

I first hypothesize that aid flows through non-state channels increase with the intensity of the climate-related disaster.

Second, I hypothesize that aid flows through state channels increase with the resources available to the recipient government beside foreign aid.

Finally, I hypothesize that aid flows through state channels increase the more the recipient government values the public good, which is assumed to be the case in more democratic political regime.

I verify the hypotheses empirically. I use a donor-recipient panel of the 40 major donors and 155 recipient countries during the period 2005-2015. This provides a sample of 46,500 observations. International responses to a disaster can take several years to materialize. It is thus important to consider the effects of climate shocks on aid delivery over time, beyond contemporaneous effects. To assess such dynamic effects, my empirical strategy follows a similar approach to a difference-in-differences identification strategy, with multiple periods and variation in treatment timing across units. I use fixed effects models to absorb any time-invariant unobservables. I also leverage quasi-random variations in the frequency and the intensity of climate extreme events to limit the influence of potential time-varying counfounders. Finally, I use the generalized event-study approach suggested by Schmidheiny and Siegloch (2023) to account for the specificity of my setting, including carryover effects due to dynamic treatment effects and non-absorbing treatments turning on-off.

The contribution of this paper are threefold. First, I extend the work by Raschky and Schwindt (2012) that show that the choice of channel of delivery for humanitarian aid is shaped by donors' strategy interests. Here, I consider both humanitarian and development aid, while further disaggregating the latter to differentiate between development and governance aid. This allows me to make connections with the literature on aid in fragile and conflict-affected settings.

Second, I contribute to the literature on the political economy of foreign aid delivery. I show that aid delivery tactics react to time-varying shocks, such as climate disasters. I extend available data on the mode of aid delivery by leveraging unstructured information on the name of the main implementing partner for projects reported to the OECD DAC. I highlight the role played by international and domestic political factors in shaping international disaster risk reduction policy.

Third, I contribute to the literature on the economics of natural disasters by suggesting an identification strategy that allows for multiple non-absorbing shocks per unit, with varying intensities. A common setting when estimating the impacts of climate extremes. I conduct several sensitivity tests to show that how choices for the empirical specification can lead to significant consequences on the results.

The rest of the paper proceeds as follows: Section 2 presents the conceptual framework, Section 3 describes the empirical strategy and the data, while section 4 presents the main results, with additional robustness checks and the heterogeneity analysis. Finally, Section 6 concludes.

Conceptual framework

The current paper relates to the literature on the policy bargaining process between providers and recipients of foreign aid. The standard approach follows a principal-agent framework, where an aid agency (principal) transfers a certain amount of resources to a recipient government (agent). When actors have different objective functions and there is information asymmetries, differences in preferences between the principal and the agent result in an agency bias creating commitment and credibility problems (Dreher, Lang, and Reinsberg 2024).

One strand of the literature stresses that negotiations do not only happen over the amount of aid, but also on the degree of control over its use. This could mean policy conditions attached to aid, seen as an aggregate (Annen and Knack 2021) or differences in the composition of aid, seen as heterogeneous and disaggregated by modalities and delivery mechanisms Swedlund (2017).

Most of this literature, however, addresses aid delivery from a donor perspective. Here, I consider the recipient perspective. I build on the theoretical framework presented in Annen and Knack (2021). They consider a situation where a recipient government maximizes its utility by choosing policy

$$p_i \epsilon [0, 1]$$

regarding the division of resources between a public good and a private good. The utility of a recipient is given by

$u_i = G_i + \phi_i(1 - p_i)R_i$

where $R_i = r_i + a_i$, i.e., the total amount of resources, consisting of domestic resources r_i and foreign aid a_i, and G_i the public good that is produced using technology,

$G_i = (p_i, R_i)^\beta$

The parameter ϕ_i captures a recipient's valuation of the public good relative to the private good. The larger ϕ_i, the more a recipient values the private good relative to the public good. The authors establish a connection with domestic political economy frameworks, such as the "selectorate framework", in which a leader's incentive to increase public goods depends on the size of the social group that she relies on to remain in power (Bueno de Mesquita et al. 2003). I go back to this connection below. Besides, the model presented by Annen and Knack (2021) assumes that the donor only cares about the public good, so that ϕ_i also measures the alignment of preferences between the donor and a recipient.

Interestingly, one can think of the parameter ϕ_i in a similar fashion to the "internal discipline" parameter in the theoretical framework by Bourguignon and Gunning (2020). Their model focuses on the way aid is delivered and the implicit conditionality in the mode of delivery(defined by a monitoring and a penalty parameters). It highlights the relationship between the mode of delivery, the recipient government's policy choice, and the way domestic political economy characteristics in the recipient country affect this relationship. The framework consider two groups with conflicting policy preferences in the population of the recipient country, that they define as the elite and the poor. The state's value both groups' utility, conceptualized has their net income per capita, but differently. Its utility function has a quasi-linear specification with a weight given to the poor by an exogenous parameter . One interpretation is that the parameter stands for the relative bargaining power of the poor group and, more broadly, encapsulates the effect of institutional features in the recipient country. Moreover, the model also assumes that the donor's preferences align with the poor, so that the parameter measures both the domestic political economy and the alignment of preferences between the donor and the recipient, similarly to the parameter ϕ_i in Annen and Knack (2021). Another interesting comparison can be made with the foreign influence framework by Aidt, Albornoz, and Hauk (2021) that considers a two-level bargaining game between a foreign power and the leader's target country, as well as between two social groups (the leader's support group and the opposition group) with conflicting policy preferences in the target country.

> *Hypothesis #1: following an external shock, the amount of aid delivered through State channels tend to increase with the intensity of the shock.*

> *Hypothesis #2: following an external shock, the amount of aid delivered through State channels tend to increase (decrease) when*

the recipient government has alternative (domestic or international) sources of funding.

Hypothesis #3: following an external shock, the amount of aid delivered through State channels tend to decrease (increase) with the bargaining power of the recipient government's social group (the elite) over the other social group (the poor).

Empirical strategy

Data

Outcomes

I use project-level aid flow data from the OECD Creditor Reporting System (CRS) covering Official Development Assistance (ODA) commitments in 2022 constant US dollar, from 2005-2023[1]. ODA can take the form of either grants or concessional loans. It excludes Other official flows (OOF), official export credits and private flows also collected by the DAC. Because I focus on cross-border ODA flows, I exclude in-donor (e.g., refugees/asylum seekers, development awareness) expenditures and administrative (non-sector allocable) costs from the analysis. Commitments represent aid planned or promised by donors.

Providers that report to the OECD include both DAC and non-DAC country members, multilateral institutions, as well as private philanthropic foundations[2]. ODA recipient countries and territories include the Least Developed Countries (LDCs) as defined by the United Nations (UN) and Low and Middle Income Countries based on gross national income per capita as published by the World Bank[3]. The list is revised every three year. As of April 2025, DAC members included 188 providers and 141 recipient countries. For this study, I look at both bilateral and multilateral donors, but I focus on the twenty largest actors in each group, giving me a sample of forty donors (see Table 6 in the *Appendix*).

According to the OECD, the channel of delivery is "*the entity that has implementing responsibility over the funds and is normally linked to the extending agency by a contract or other binding agreement, and is directly accountable to it*". The channel of delivery became an optional reporting item on the new CRS++ reporting scheme in 2004 (Dietrich 2013) and is thus not available before. Even after this date many observations in the dataset include missing information. To impute missing data I leverage unstructured information from an additional variable in the dataset where providers can manually report the name or type of partner though which the project is implemented. Moreover, for

[1] I use the last updated version of the project-level CRS dataset from September 22, 2025.

[2] Not all providers of development cooperation report their activities to the DAC. For instance, non-DAC "emerging donors" such as China and Brazil provide what they refer to as "South-South cooperation" but do not report it to the DAC.

[3] the DAC list of ODA Recipients excludes former G8 members, EU members, and countries with a firm date for entry into the EU.

the remaining missing data, I use information on the type of modality to code budget support with a missing channel as aid delivered through the recipient's state institutions (see the Appendix for more information on the imputation methodology).

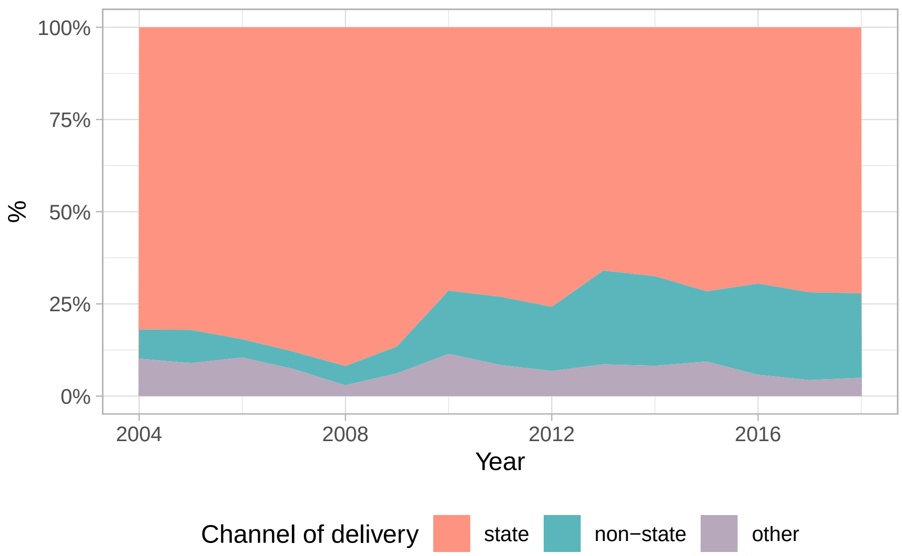


Figure 1

I classify aid flows into two categories based on the implementing agency: (1) state and (2) non-state. There is wide heterogeneity within the non-state channel group. However, this classification captures the fundamental distinction between on-budget, government-executed aid and off-budget assistance that bypasses recipient institutions. I also examine this subgroup variation in the "Heterogeneity" section.

Three types of outcome variables are used in the analysis: (1) the overall volume of ODA commitments; (2) the ODA commitments delivered through a State channel; (3) the ODA commitments delivered through a non-State channel. They are in 2022 constant US dollar. The channel of delivery is the first implementing partner. It is the entity that has implementing responsibility over the funds and is normally linked to the extending agency by a contract or other binding agreement, and is directly accountable to it. In the case of loans, the borrower is reported as the first implementing partner, i.e. the first entity outside the donor country that receives the funds. State implementing partners (*State channels*) include public sector institutions in the recipient country. Non-State implementing partners (*non-State channels*) include both official and private actors. Official actors include UN agencies and Multilateral Development Banks

Table 1: Purposes by channel of delivery, in percentages (%)

	Channel			
	state	non-state	other	Total
Development	81.0	13.3	5.7	100
Governance	60.5	23.7	15.8	100
Humanitarian	21.6	65.2	13.2	100
Other	17.6	62.7	19.7	100
Ensemble	**74.5**	**18.1**	**7.3**	**100**

[a] Note: Governance aid includes projects with sector codes 151 and 152. Development aid includes sector codes between 110 and 600 (excl. codes 151 and 152). Humanitarian aid includes sector codes 700.

(MDBs). Non-official actors include Non-Governmental Organizations (NGOs) and private companies.

Treatment

Disaster events come from EM-DAT compiled by the Centre for Research on the Epidemiology of Disasters (CRED) (Delforge et al. 2025). The database systematically records global disaster data since 1988 from various sources, including UN agencies, non-governmental organizations, reinsurance companies, research institutes, and press agencies. To be included in EM-DAT, an event must meet at least one of the following criteria: (i) 10 deaths or above; (ii) 100 people affected or above; (iii) A call for international assistance or a declaration of a state of emergency. I select four types of disasters related to weather and climate extreme events: floods, droughts, storms and heatwaves (Figure 2).

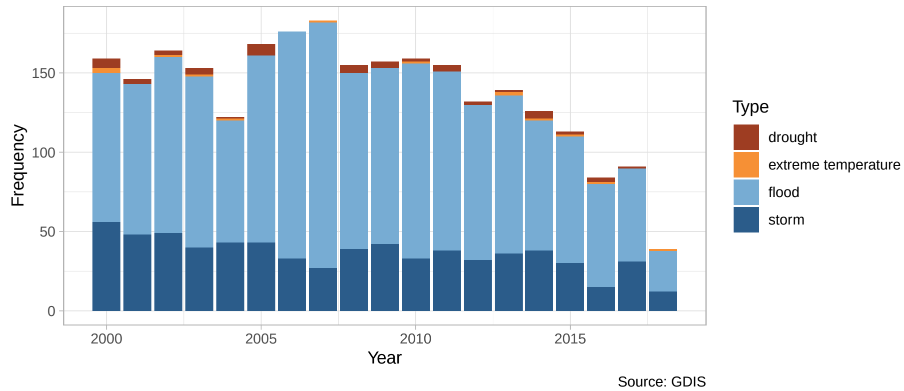


Figure 2: Climate-related disaster events, 2000-2018

To avoid endogeneity bias related to the disaster-related socioeconomic losses and damages reporting, I build a physical measure of exposure to hazard intensity in a similar approach than Dellmuth et al. (2021). The measure combines geocoded spatial information on disasters and climate extreme indices based on gridded meteorological data. It has an easy interpretation as the average number of daily extreme events an individual is exposed to in a given year.

Geocoded spatial information on disasters come from the GDIS dataset (Rosvold and Buhaug 2021). For each event listed in EM-DAT between 1960 and 2018, GDIS provides geocoded data as spatial geometries (polygons) at the administrative level 1 (ADM-1) or lower. For consistency, I use spatial geometries at ADM-1 because not all entries in GDIS share the same granularity.

Gridded meteorological data come from ERA5 reanalysis (Muñoz-Sabater et al. 2021). ERA5 atmospheric reanalysis provides hourly data on surface and upper-air parameters with global coverage at 0.25° (31x31 km at the equator) that covers the period from 1979 to the present. It is produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) on behalf of the European Union's Copernicus Climate Change Service (C3S). To build hazard-specific physical intensity measures, I consider three different parameters: daily total precipitation (floods and droughts), daily mean wind (storms), and daily mean temperature (heatwaves). I crop the gridded climate data to the boundaries of each of the selected ADM-1 regions in GDIS. I build climate indices from the grid-level daily weather data (Table 2).

Next, I construct intensity measures based on the annual frequencies of extreme events, defined as deviations of grid-level daily climate indices from their historical norms. This approach builds on the climate science literature on indices of extremes (Zhang et al. 2011; IPCC 2021) and is common in climate econometrics for single-hazard measures (Hsiang 2016). It calculates the number of days in a year exceeding thresholds that are relative to a base period climate.

Table 2: Hazard intensity index

EMDAT	ERA5	Indice
flood	daily total precipitation	5-day cumulative precipitation
drought	daily total precipitation	180-day cumulative precipitation
storm	daily mean wind	daily mean wind
heatwave	daily max. temperature	5-day average max. temperature

Here, I use a relative threshold of 95th-percentile and a base period from 1980 to 2000[4]. The intuition behind the intensity measure is that the more daily extreme events in a year, the more likely they are to cause socioeconomic damages leading to a disaster.

I average these annual intensity measures at the administrative level assigned to each disaster event using population weights from the 2000 Landscan dataset (Bright and Coleman, n.d.). These country-year climate-disaster intensity measures have the advantage to take into account the specificity of each local climates but remain at the same time comparable across geographies and event types. They are also good predictors of a disaster's occurrence.

Covariates

For the government (tax) revenues, I use the International Monetary Fund's World's Revenue Longitudinal Database (WoRLD) that gathers 32 years (1990-2022) of tax and non-tax revenues for 190 IMF member countries. For information on the political regime, I use the Democracy Indices from the V-Dem database.

Empirical specification

This study aims to estimate the dynamic response of annual channel-specific aid flows, from a donor d to a recipient r, to the climate hazards-related disasters exposure in recipient r in a given year t.

For a panel with an observation window for the outcome $T = [\underline{t}, \overline{t}]$, with an effect window restricted to the time interval $J = [\underline{j}, \overline{j}]$ that considers $\overline{j} > 0$ years after the disaster event and $\underline{j} < 0$ years before it, the baseline specification is the following:

$$Y_{drt} = \alpha_{dr} + \tau_t + \sum_{j=\underline{j}}^{\overline{j}} \beta_j \mathbb{D}^j_{rt} + \sum_{z \in Z} \beta_z X_{zdrt} + \epsilon_{drt}$$

[4] Percentile thresholds allow to preserve non-linearities, while constructing a measure that is evenly distributed. Defining a base period is consistent with assuming that individuals form climate beliefs over the length of this historical distribution and any deviations from it would constitute unexpected idiosyncratic shocks (Carleton 2024).

where Y_{drt} is the ODA flows from donor d to recipient r at year t. α_{dr} are donor$\times$recipient pair fixed effects and τ_t are year fixed effects. X'_{drt} is a vector of the additional fixed effects and covariates included in alternative specifications. I use period $t-1$ for the reference period and therefore drop its treatment indicator. Standard errors are cluster-robust, with clustering at the recipient-country level. The error term is denoted by ϵ_{drt}.

One constraint of the approach suggested by Schmidheiny and Siegloch (2023) is that one needs to observe the treatment status for a wider period than the outcome (see Figure 5). As mentioned above, the observation window for treatment status is restricted between 2000 and 2018. This limits the observation window available for the dependent variable. In the baseline specification, I consider an effect window $J = [-3, 5]$ consistent with the literature[5]. This restricts my sample period from 2000-2018 to 2005-2015.

The estimand is a proportional treatment effect (i.e. a semi-elasticity). It is the percentage change in donor-recipient dyadic aid flows due to the recipient's exposure to disasters. In my setting, the outcome variables are non-negative[6] and non-normally distributed. It is common practice in this case to use "log-like" OLS transformations of the outcome (Osberghaus 2019).

However, log-OLS models can yield biased estimates under heteroskedasticity (Silva and Tenreyro 2006). Besides, the large number of zeros in the dependent variable leads to a truncated sample under log-transformation (Head and Mayer 2014; Mullahy and Norton 2024) and extensive margin effects create an arbitrary dependence with the units of the outcome (Chen and Roth 2024). Chen and Roth (2024) recommend instead to use Poisson regressions or to estimate separate effects for the two margins[7].

Identification strategy

I follow a similar approach to a difference-in-differences identification strategy, with multiple periods and variation in treatment timing across units. A first identifying assumption is that, conditional on observables and time-invariant unobservables, the treatment is as good as randomly distributed (strict exogeneity

[5] Yang (2008) includes four lags in his main specification, besides the contemporaneous effect. David (2011) and Becerra, Cavallo, and Noy (2015) consider 6-period and 5-period windows to estimate their VAR models, respectively. Becerra, Cavallo, and Noy (2014) uses a [-7;7] window. They find that foreign aid increases in the aftermath of large natural disasters, but stabilize in the following periods. Adopting a local-projection method, Arezki et al. (2025) consider a [-10;10] window and find that dynamic responses last less than 5 years.

[6] Foreign aid withdrawals as a type of punitive decision and ex-post political conditionality exist, but they remain rare events.The *threat* of withdrawal is, however, an important factor to consider in the political economy of international development assistance (Cheeseman, Swedlund, and O'Brien-Udry 2024).

[7] The authors also show that the marginal effects implied by two-part models, commonly used in the foreign aid allocation literature, do not correspond with Average Treatment Effects (ATE) for the intensive margin. The recommend instead to use Lee-type bounds (Lee 2009). However, such approaches require additional identifying assumptions.

assumption). Another related assumption is that the outcome of the treated and untreated units would have evolved in parallel in absence of the treatment (parallel-trends assumption). Based on these assumptions, my estimation strategy uses fixed effects models to absorb any time-invariant unobservables. I also leverage quasi-random variations in the frequency and the intensity of climate extreme events to limit the influence of potential time-varying counfounders.

First, the baseline specification includes *donor-recipient fixed effects* to eliminate any time-invariant (as well as slow-moving) attributes of recipients and of their bilateral relationships with donors. I also include *year fixed effects* to absorb common shocks in a given year, that could affect both the aid flows received by a country and its probability to be affected by a climate hazards-related disaster. Finally, I use *recipient-specific linear time trends*. In alternatives specifications, I replace linear trends with time-varying covariates such as donor overall aid commitments, recipient GDP and population levels. I also replace year fixed effects by *donor-year fixed effects* following Faye and Niehaus (2012) and Arezki et al. (2025), and by *region-specific year fixed effects* and *recipient-specific linear trends*, in the spirit of Yang (2008).

Second, I exploit quasi-random variation in the occurrence of climate extreme events to differentiate disaster events by their varying intensities. This helps address the treatment homogeneity assumption (Sun and Abraham 2021). The empirical literature on the response of foreign aid to disasters also show that foreign aid is sensitive to the intensity of hazards, more than just their occurrence (Becerra, Cavallo, and Noy 2014). However, measures of disaster severity based on socioeconomic losses and damages are prone to endogeneity bias (Kahn 2005; Toya and Skidmore 2007; Jones, Guha-Sapir, and Tubeuf 2022). Disasters are social phenomena caused by structural factors that create vulnerability to the impacts of hazards. Such structural factors also influence the allocation of foreign aid. Fixed effects models don't remove bias from unobserved time-varying counfounders. Physical measures of disaster intensity reduce the influence of time-varying unobservables in causal empirical analysis (Noy 2009; Cavallo et al. 2013; Felbermayr and Gröschl 2014; Felbermayr et al. 2022; Botzen, Deschenes, and Sanders 2019).

Following this approach, I assume that short-term, time-varying, factors are more likely to affect hazard impacts rather than occurrence or exposure. For example, Caso, Hilhorst, and Mena (2023) find that disasters occur 5% more often in armed conflict settings than in situations without conflict, while yearly disaster-related deaths were 34% higher. Nevertheless, the main threat to identification lies in shocks at the level of treatment (recipient country) that affect the occurrence of disasters and foreign aid flows.

Furthermore, there are two additional challenges for identification in this setting: carryover effects due to dynamic treatment effects and non-absorbing treatments turning on-off. Due to coordination costs, commitments by donors to support reconstruction and rehabilitation efforts can take several years to materialize. This creates a time lag between the occurrence of a disaster and the response by the international community. When current treatments influence future outcomes (carryover effects) it biases the comparison between treated and untreated units. To account for such dynamic treatment effects, I adopt a non-parametric event-study design.

Besides, most recipient countries in the sample are affected by multiple disasters over the sample period (Figure 3). To account for both carryover effects and non-absorbing treatments, I apply distributed-lag models in the general case, with multiple events with varying intensities, presented by Schmidheiny and Siegloch (2023)[8]. The author show that event study models with binned endpoints and distributed-lag models yield identical parameter estimates. Distributed-lag models have the advantage to be less error-prone. This approach makes the additional assumption that dynamic treatment effects stabilize outside the effect window (effect stabilization assumption). In robustness, I use the imputation (or counterfactual) estimator robust to heterogeneous treatment effects built by Gardner (n.d.).

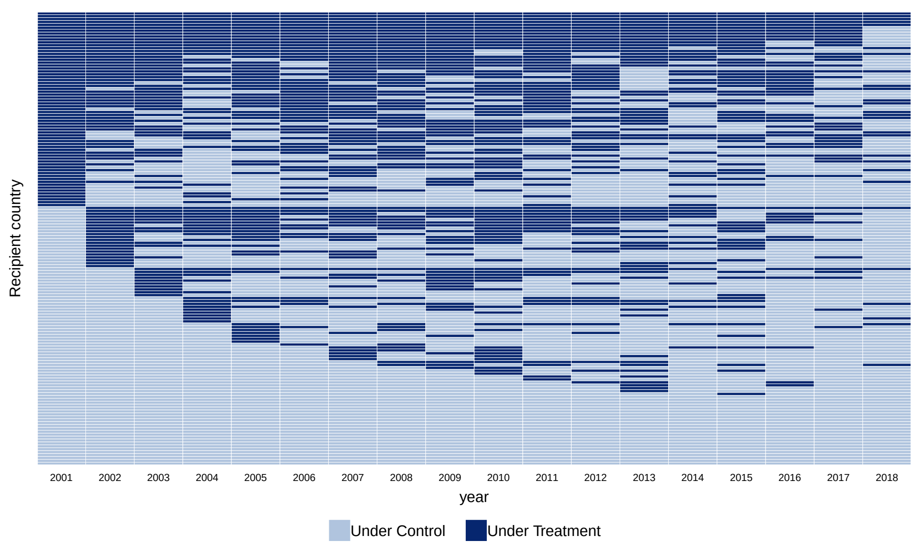


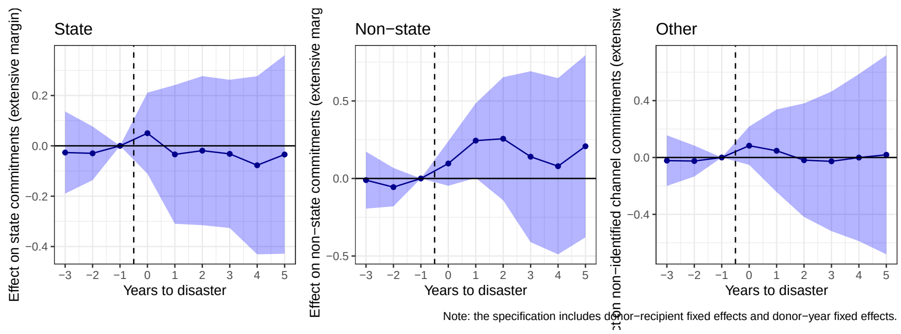
Figure 3: Treatment paths

Results

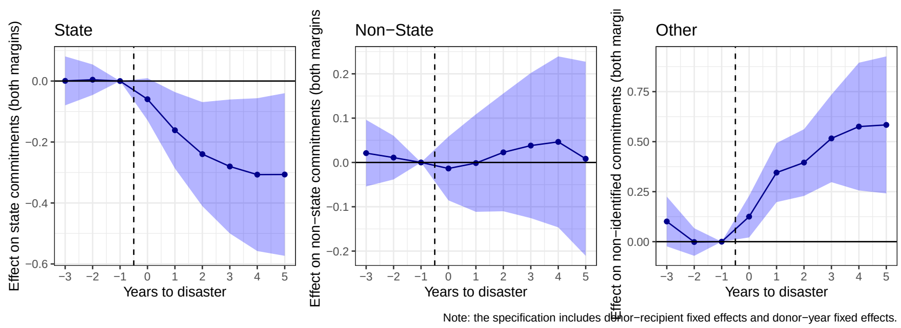
Baseline results (total aid)

Binary outcome (extensive margin)

[8]It is also similar to the Multiple Dummies On (MDO) approach by Sandler and Sandler (2014) where event variables are not mutually exclusive.



Continuous outcome (both extensive and intensive margins)



Disaggregated by purposes

Table 3: Summary Statistics, by channel of delivery

sect_hum		Mean	SD	Min	Max
Outcome					
Development	ODA total	14.61	101.10	0.00	6449.56
	ODA State	9.91	86.09	0.00	6303.84
	ODA non-State	2.68	23.77	0.00	2903.40
Humanitarian	ODA total	1.57	31.67	0.00	7561.98
	ODA State	0.28	25.38	0.00	7561.98
	ODA non-State	1.17	17.73	0.00	1085.89
Other	ODA total	0.07	2.79	0.00	340.58
	ODA State	0.04	2.49	0.00	340.58
	ODA non-State	0.02	0.88	0.00	170.64
Treatment					
	Disaster dummy	0.39	0.49	0.00	1.00
	Intensity index	0.08	0.45	0.00	7.03

Humanitarian aid

	State		Non-state
Binary	Continuous	Binary	Continuous

Development aid

	State		Non-state
Binary	Continuous	Binary	Continuous

Robustness

- Alternative fixed-effects structures
- Binary treatment
- Long-effect window
- Counterfactual/imputation estimator (Liu, Wang, and Xu 2024; Borusyak, Jaravel, and Spiess 2024; Gardner, n.d.)
- Alternative climate extreme indices assumption (indice, historical distribution, percentile threshold)
- Disbursements

Heterogeneity

- Treatment:
  - Large disasters (75th-pct)
  - Fast-onset vs. Slow-onset events
  - Exposure: built-up area, agricultural land (MODIS)
- Outcome:
  - Non-state channels: official (multilateral organizations) vs non-official (private sector)
- Recipients:
  - Government total (incl. tax) revenues
  - Political regime (autocracy-democracy)
  - State capacity (territorial control)
  - Political stability (active armed conflicts)
- Donors:

  - Bilateral/Multilateral
  - Statist/Market-oriented (Dietrich 2021)
- Donor-recipient relationship: geopolitical alignment

Conclusion

Appendix

Table 6: List of donor sample

donor_name	total	rank	pct_cum
International Development Association	252928.875	1	0.2627986
EU Institutions	175576.896	2	0.4452268
Japan	145977.641	3	0.5969007
Germany	120977.969	4	0.7225995
Global Fund	44078.785	5	0.7683983
United Kingdom	42654.995	6	0.8127177
Canada	22396.348	7	0.8359880
African Development Fund	20915.657	8	0.8577199
Australia	20455.585	9	0.8789737
IMF (Concessional Trust Funds)	20431.184	10	0.9002021
Spain	15474.780	11	0.9162807
Netherlands	13515.907	12	0.9303240
Sweden	13154.945	13	0.9439923
Switzerland	12889.178	14	0.9573845
Italy	12300.398	15	0.9701648
Belgium	10340.500	16	0.9809088
UNRWA	7583.883	17	0.9887887
Global Environment Facility	6692.261	18	0.9957421
Finland	4098.023	19	1.0000000

Table 7: List of recipient countries

Name	Cohort
Afghanistan	2004
Albania	2004
Algeria	2004
Angola	2004
Anguilla	2007

(continued)

Name	Cohort
Antigua and Barbuda	2004
Argentina	2004
Armenia	2004
Azerbaijan	2004
Bahrain	2004
Bangladesh	2004
Barbados	2004
Belarus	2005
Belize	2004
Benin	2004
Bhutan	2004
Bolivia	2004
Bosnia and Herzegovina	2004
Botswana	2004
Brazil	2004
Burkina Faso	2004
Burundi	2004
Cabo Verde	2004
Cambodia	2004
Cameroon	2004
Central African Republic	2004
Chad	2004
Chile	2004
China (People's Republic of)	2004
Colombia	2004
Comoros	2004
Congo	2004
Cook Islands	2004
Costa Rica	2004
Croatia	2004
Cuba	2004
Côte d'Ivoire	2004
Democratic People's Republic of Korea	2004
Democratic Republic of the Congo	2004
Djibouti	2004
Dominica	2004
Dominican Republic	2004
Ecuador	2004
Egypt	2004
El Salvador	2004

(continued)

Name	Cohort
Equatorial Guinea	2004
Eritrea	2004
Eswatini	2004
Ethiopia	2004
Fiji	2004
Gabon	2004
Gambia	2004
Georgia	2004
Ghana	2004
Grenada	2004
Guatemala	2004
Guinea	2004
Guinea-Bissau	2004
Guyana	2004
Haiti	2004
Honduras	2004
India	2004
Indonesia	2004
Iran	2004
Iraq	2004
Jamaica	2004
Jordan	2004
Kazakhstan	2004
Kenya	2004
Kiribati	2004
Kosovo	2009
Kyrgyzstan	2004
Lao People's Democratic Republic	2004
Lebanon	2004
Lesotho	2004
Liberia	2004
Libya	2005
Madagascar	2004
Malawi	2004
Malaysia	2004
Maldives	2004
Mali	2004
Marshall Islands	2004
Mauritania	2004
Mauritius	2004

(continued)

Name	Cohort
Mayotte	2006
Mexico	2004
Micronesia	2004
Moldova	2004
Mongolia	2004
Montenegro	2004
Montserrat	2006
Morocco	2004
Mozambique	2004
Myanmar	2004
Namibia	2004
Nauru	2004
Nepal	2004
Nicaragua	2004
Niger	2004
Nigeria	2004
Niue	2004
North Macedonia	2004
Oman	2004
Pakistan	2004
Palau	2004
Panama	2004
Papua New Guinea	2004
Paraguay	2004
Peru	2004
Philippines	2004
Rwanda	2004
Saint Helena	2006
Saint Kitts and Nevis	2004
Saint Lucia	2004
Saint Vincent and the Grenadines	2004
Samoa	2004
Sao Tome and Principe	2004
Saudi Arabia	2004
Senegal	2004
Serbia	2004
Seychelles	2004
Sierra Leone	2004
Solomon Islands	2004
Somalia	2004

(continued)

Name	Cohort
South Africa	2004
South Sudan	2011
Sri Lanka	2004
Sudan	2004
Suriname	2004
Syrian Arab Republic	2004
Tajikistan	2004
Tanzania	2004
Thailand	2004
Timor-Leste	2004
Togo	2004
Tokelau	2004
Tonga	2004
Trinidad and Tobago	2004
Tunisia	2004
Turkmenistan	2004
Turks and Caicos Islands	2006
Tuvalu	2004
Türkiye	2004
Uganda	2004
Ukraine	2005
Uruguay	2004
Uzbekistan	2004
Vanuatu	2004
Venezuela	2004
Viet Nam	2004
Wallis and Futuna	2006
West Bank and Gaza Strip	2004
Yemen	2004
Zambia	2004
Zimbabwe	2004

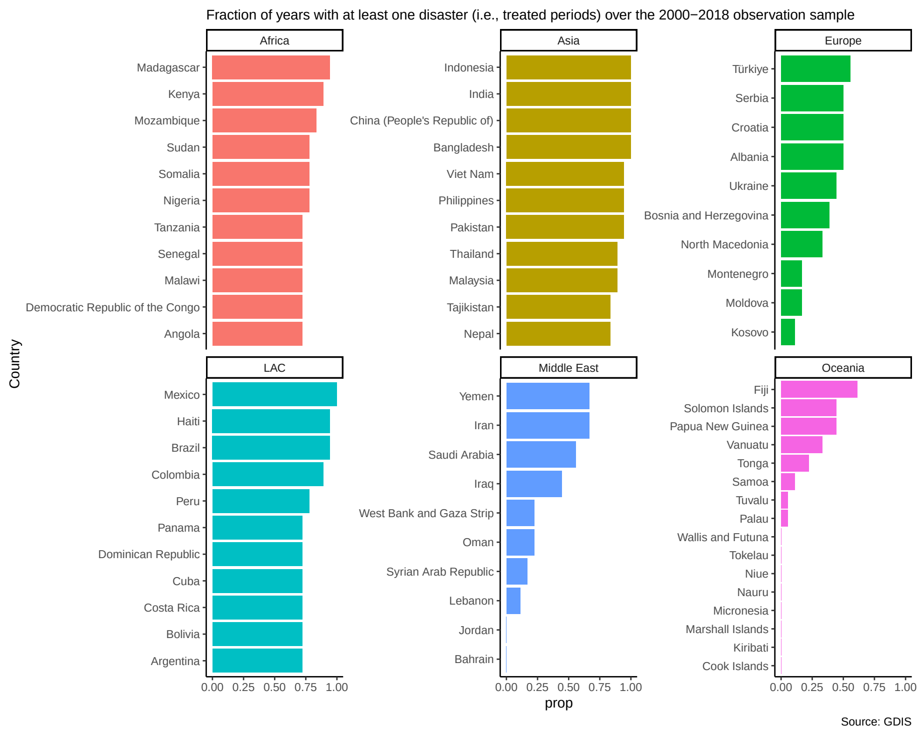


Figure 4: Top 10 country exposure to climate-related disasters, by region

For a given balanced panel of the dependent variable from $[\underline{t}, \bar{t}]$ *and a limited effect window* $[\underline{j}, \bar{j}]$*, we need to observe events from* $\underline{t} - \bar{j} + 1$ *to* $\bar{t} + |\underline{j}| - 1$*. If events are derived from changes in policy variables we need to observe treatment status from* $\underline{t} - \bar{j}$ *to* $\bar{t} + |\underline{j}| - 1$*. The following figure visualizes the required width of the observation window for a given limited effect window.*

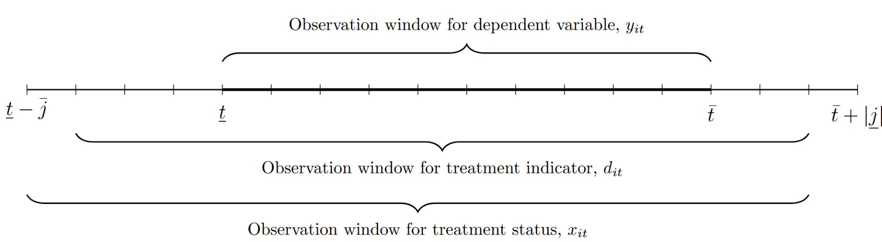


Figure 5: Data requirements (from Schmidheiny and Siegloch 2023)

Table 8: Example of information on the channel of delivery for a sample of observations (project-level)

channel_code_unique	channel_name	channel_reported_name	channel_level
41122	United Nations Children's Fund	Unicef - United Nations Children's Fund	3
10000	Public Sector Institutions	Public Sector Institutions	2
22000	Donor Country-Based Ngo	NA	2
51000	University, College Or Other Teaching Institution, Research Institute Or Think-Tank	Higher Education Institution	1
12000	Recipient Government	Recipient Government	2
90000	Other	Charles Kendall & Partners Ltd	2
10000	Public Sector Institutions	NA	2
12000	Recipient Government	Coraf, Pafasp,Firca,Arcn	2
12000	Recipient Government	Recipient Government	2
90000	Other	NA	2

Channel of delivery: imputation methodology

The OECD uses a three-level hierarchical typology to classify channels of delivery. Each category include specific codes. The first channel category include the 'channel parent category' and the second level includes sub-groups of parent categories. Depending of the channel category, the third level includes either the *type* of implementing partner (ex: 'Pension Funds' in 'Private sector' of the provider country) or the *name* of a specific actor (ex: the 'African Development Bank' in 'Regional Development Bank').

The dataset includes four variables related to the channel of delivery: `parent_channel_code` (level 1), `channel_code` and `channel_name` (level 2 or 3), and `channel_reported_name` (no specfiic level). For level consistency, I create a unique code variable `channel_code_unique` using the most granular level when both `parent_channel_code` and `channel_code` are provided.

Information on delivery channels has been updated over time. So implementing partners may be coded and described differently across time and space within the dataset. For time consistency, I apply the latest code and name list provided by the OECD (last updated in April 2025)[9].

There is a high share of missing information on the mode of delivery between 2004 and 2006, the year where the new reporting policy was implemented within the OECD DAC.

[9]The Excel file can be found here.

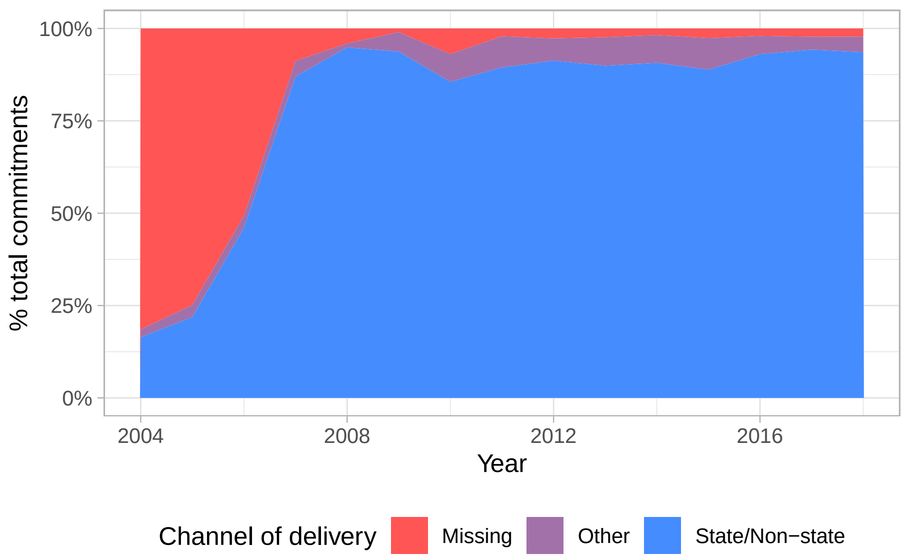


Figure 6: Missing data in channel of delivery (before imputation)

The imputation methodology is twofold. First, for projects with missing channel of delivery, I check the `channel_reported_name` variable to see if the provider reported a channel name as text. more than half of the commitments for which the channel of delivery code is missing have a name reported to the OECD DAC. Such names are usually very precise as they provide the specific name of the primary implementing partner, but they are not systematically reported. They include typos and sometimes abbreviations with no established typology to refer to. When a project with missing channel of delivery has a channel reported name (1,500 unique reported names), I hand-code the channel category[10].

Second, for remaining missing observations, I leverage information on the project's modality. Action relating to debt and General Budget Support concentrate around 60% of the commitments with missing code for the channel of delivery. I consider budget support (DAC 5 code 510) and actions relating to debt (DAC 5 code 600) as aid activities delivered through the recipient government. A significant component of aid activities where actions relating to debt following the Heavily Indebted Poor Countries initiative in 2005. Some assistance were used to reduce debt stock owed by recipient government to other providers. In such cases, non-state actors are sometimes reported as the main implementing partner. However, it is not clear if this should be accounted as an activity delivered through state or non-state channels. In the robustness section, I conduct the analysis excluding actions relating to debt.

[10]A table with channel reported names, imputed channel category, and the rationale for the imputation will be made available in the replication package.

Table 9

sector_name	sector_code	total_amount	na_amount	share_na	cumsum
VII. Action Relating to Debt	600	43390.13	15382.637	0.2051505	21
VI.1. General Budget Support	510	52571.06	13633.139	0.1818183	39
I.5.a. Government & Civil Society-general	151	85639.60	7213.624	0.0962045	48
I.1.b. Basic Education	112	22409.38	7097.815	0.0946600	58
II.1. Transport & Storage	210	119385.77	4472.825	0.0596518	64

Top 5 sector with the highest commitments with missing code for the channel of delivery

Overall, the imputation procedure allows to solve the missing data issue with original data extracted from OECD DAC.

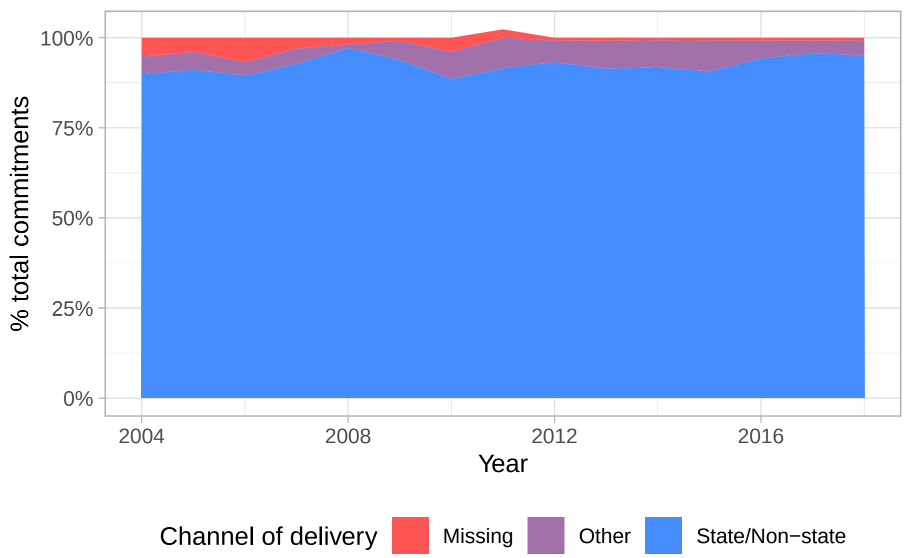


Figure 7: Missing data in channel of delivery (after imputation)

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