Beg or bargain? The impact of climate-related disasters on foreign aid delivery

Early draft, please do not circulate *

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Abstract

Climate disasters increasingly disrupt development trajectories, yet how these shocks alter the distribution of aid across delivery channels remains poorly understood. I examine whether exposure to climate-related shocks reshapes aid allocation using a generalized event-study design that exploits exogenous variations in local climates. Using geospatial disaster data and grid-level weather information to construct measures of multi-hazard physical exposure, I find that disaster shocks trigger a significant increase in non-state development aid alongside a partial substitution of state-led flows. Crucially, however, governance aid to state institutions increases significantly following shocks. Results suggest a post-disaster equilibrium that serves the dual objectives of risk mitigation for donors and political stability for recipients. These findings underscore how complementarity across aid interventions is a strategic asset in international cooperation.

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Introduction

International cooperation following a disaster is a game of mutual dependence. Donors face incentives to mitigate the cross-boundary spillovers of localized shocks, through regional instability or supply chain disruptions, while recipient governments strategically leverage these global risks to secure external funding. This interdependence defines the bargaining over aid modalities. In stable times, this bargain is anchored in long-term institutional quality and geopolitical alignment. However, we lack an understanding of how exogeneous shocks impact the choice of implementing partner.

This paper investigates whether climate-related disasters catalyze a shift in aid delivery. Focusing on the tension between state and non-state delivery channels, I examine whether climate-related disasters systematically alter the composition of bilateral aid flows.

Using a comprehensive bilateral donor-recipient panel from 2005-2015, disasggregated by aid activities, I exploit quasi-random variations in the frequency and intensity of climate extreme events within a generalized event-study framework. I find three key results: (i) climate disasters trigger significant increases in non-state development aid, (ii) this shift coincides with a partial substitution away from state-led flows, and (iii) governance aid to state institutions increases following the shock, suggesting a complementary rather than substitutive relationship between channels. Notably, I find no significant effect on bilateral humanitarian aid, pointing to potential free-rider problems in emergency response.

The paper makes three main contributions. First, I contribute to the literature on foreign aid instruments and modalities (Raschky and Schwindt 2012; Dietrich 2013; Knack 2013; Acht, Mahmoud, and Thiele 2015; Dreher, Langlotz, and Marchesi 2017) by demonstrating that the selection of delivery channels is a dynamic response to external shocks rather than simply a mere reflection of institutional settings. I provide novel empirical evidence by leveraging unstructured data on the channel of delivery for projects reported to the OECD DAC.

Second, I advance the disaster economics literature (Yang 2008; David 2011; Becerra, Cavallo, and Noy 2014, 2015; Osberghaus 2019) on two methodological grounds. Firstly, I use a generalized event-study approach that accounts for multiple non-absorbing treatments per units, to show that disasters mostly have short-term dynamic effects. These results suggest that failing to consider multiple events can lead to an overestimation of dynamic effects. Secondly, I combine gridded weather and geolocalized disaster records to construct multihazard measures of recipient countries' physical exposure to climate disasters.

Finally, I link the aid negotiation literature (Mosley 1987; Whitfield and Fraser 2010; Swedlund 2017; Zeitz 2024) to disaster response. I provide empirical evidence of a "complementarity of channels" equilibrium, where donors and recipi-

ents reach bargaining outcomes that strategically combine non-state implementation of development activities with state-focused institutional strengthening. This complementarity allows recipient governments to concede operational control over service delivery in exchange for state capacity building, while donors maintain influence through both direct implementation and institutional reform.

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

Conceptual framework

Donor's menu of strategies

Foreign aid provides geopolitical benefits to donors (Bau and Dietrich 2025; Thiele et al. 2025). The latter face a two-dimensional policy space when designing their foreign aid strategy:

Intervention type—There are two distinct yet complementary intervention strategies (Aidt, Albornoz, and Hauk 2021). First, *policy interventions* focus on immediate public service delivery, whether through humanitarian relief (humanitarian aid) or economic stabilization (development aid). Second, *institution interventions* target the recipient country's institutional framework rather than immediate service delivery. These interventions either aim to reinforce state capacity or empower non-state actors such as civil society organizations (governance aid).

Importantly, policy and institution interventions are not mutually exclusive. Donors can pair aid delivered through non-state channels for swift implementation of relief efforts with parallel governance programs designed to achieve long-term institutional alignment.

Channel of delivery—The choice of implementing partner reflects a delegation dilemma (Marchesi, Sabani, and Dreher 2011; Dreher, Langlotz, and Marchesi 2017). This is particularly true in the context of disaster response. State channels (e.g., public institutions) offer local ownership and align with existing institutions but risk agency slack or aid capture. In contrast, non-State channels (e.g., NGOs, multilateral organizations, private contractors) mitigate capture risks, yet they incur sovereignty costs (eroding public administration monopoly) and accountability costs (weakening state legitimacy in public services provision).

Empirical evidence shows that donors delegate to state institutions when recipient governments exhibit high capacity and aligned incentives, minimizing transaction costs while maximizing influence. Conversely, in weak or misaligned institutional environments, donors accept the higher costs of non-state channels

as a premium to circumvent dysfunctional bureaucracies (Dietrich 2013, 2021; Knack 2013, 2014; Acht, Mahmoud, and Thiele 2015).

Aid policy bargaining

The relationship between aid agencies and recipient governments is a dynamic negotiation process[1]. Both parties aim to reach an agreement, albeit with divergent objectives. Aid providers seek to exert influence over domestic policy in recipient countries, while recipient governments prioritize access to low-cost external finance to secure political survival (Mosley 1987; Mosley, Harrigan, and Toye 1995; Whitfield 2009; Whitfield and Fraser 2010; Swedlund 2017; Winters 2024).

The relative negotiating power of each party is constrained by their structural conditions and fallback options. The donor's leverage stems from its control over scarce resources and the opportunity cost of reallocating aid to alternative recipients (Annen and Knack 2021). Meanwhile, the recipient's bargaining position depends on its ability to secure external finance on favorable terms or generate domestic revenue through taxation (Queralt 2022). These asymmetries define the boundaries of possible agreements, where the provider's ideal point maximizes policy influence at minimal financial cost, and the recipient's ideal point secures maximal, unconditional resources.

Disasters as shocks to the bargaining agreement

Climate-related disasters[2] act as external shocks that disrupt the aid bargaining process by altering the opportunity costs and incentives for both donors and recipients. These shocks generate cross-border spillovers (international level) and demands for relief and reconstruction (domestic level). This forces a renegotiation of aid terms, as the status quo becomes unsustainable for both parties (Killick 1998).

Recipient-side

Disasters can impose two types of shocks on recipient governments (Bueno de Mesquita and Smith 2017). First, *revenue shocks* (extensive margin) reduce

[1] As highlighted by Killick (1998), "*(…) to assert the frequency of interest conflicts it is not necessary to imply a confrontational view of donor—government relations.*" (p. 91).

[2] The United Nations Office for Disaster Risk Reduction defines a disaster as "serious disruption of the functioning of a community or a society at any scale due to hazardous events interacting with conditions of exposure, vulnerability and capacity, leading to one or more of the following: human, material, economic and environmental losses and impacts" (UNDRR 2017).

available resources, tightening budget constraints and threatening political survival. Second, *policy shocks* (intensive margin) reallocate spending toward immediate relief and reconstruction, crowding out patronage.

There are two resulting dynamics: (i) the demand for external finance rises due to higher relative costs of domestic taxation ; (ii) despite a preference for state channels to retain ownership, non-state channels emerge as a second-best option to relax budget constraints when state capacity is overwhelmed.

Three factors mediate the impact of disaster shocks on a government's response:

Domestic politics—Constraints on the executive and civil society participation increase the internal pressure for government responsiveness and limit leaders' ability to extract rents. In systems with low internal discipline, leaders can allocate resources towards private goods with minimal oversight, reducing their incentive to provide public goods such as disaster relief (Plümper and Neumayer 2009; Flores and Smith 2013). Conversely, high internal discipline forces leaders to prioritize the provision of public goods to maintain state legitimacy.

Fiscal capacity—The government's administrative capacity to mobilize domestic resources through taxation expands the resource base and improves self-sufficiency. However, increasing taxes can lead to domestic contestation in the form of opposition to revenue extraction (especially after a disaster) or greater taxpayer monitoring, which reduces a leader's discretionary power. Taxation also requires costly long-term bureaucratic reforms, with decreasing marginal investment costs (Queralt 2022). Consequently, the lower a country's fiscal capacity, the more climate shocks force leaders to sacrifice control over aid implementation to ensure regime solvency.

Alternative sources of external finance—A country's international status in the global system determines its access to external finance, including non-DAC donors (e.g., China) and private capital markets. Access to alternative sources of funds strengthens a country's bargaining position in negotiations with donors (Zeitz 2024). Multilateral institutions can mitigate this effect by acting as a collective insurance mechanism. In these settings, a strategic substitution effect might occur, whereby bilateral donors, faced with high transaction costs and coordination problems, delegate implementation to multilateral agencies to leverage their specialized expertise and economies of scale (Annen and Knack 2018).

Donor-side

Disasters trigger *cross-border externalities* that compel donor action. These shocks increase incentives for policy intervention to help the recipient government internalise negative spillovers, whether economic (e.g., trade disruptions), humanitarian (e.g., refugee flows), or geopolitical (e.g., regional instability) (Bermeo 2017, 2018). However, post-disaster environments introduce high transaction costs and coordination problems, with heightened risks of agency

slack and aid capture. To mitigate these risks, donors often opt for non-state channels (e.g., NGOs, multilaterals). They can pair with governance-focused state aid to balance immediate relief with long-term state-building.

Besides, disasters in recipient create a "window of opportunity" to exert influence on recipient countries' *political alignment* (Cheng and Minhas 2021). Shocks create a temporary leverage advantage for donors, as recipients' heightened demand for external finance lowers the opportunity cost of institution interventions. Donors can allocate governance aid through state channels to complement non-state policy interventions in order to get recipient leader's support. Or, donors can provide non-state governance aid to support internal discipline through civil society participation if recipient leader preferences are not aligned with donors.

The conceptual framework suggests two main hypothesis:

- *Hypothesis #1: The volume of development aid channeled through non-state actors increases with the intensity of a climate-related disasters.*
  - *Hypothesis #1bis: the shift to non-state channels in development aid is most pronounced when the recipient is an autocratic regime with low internal discipline.*
- *Hypothesis #2: The volume of governance aid increases with the intensity of a climate-related disasters.*
  - *Hypothesis #2a: The volume of governance aid channeled through state actors increases more when the recipient is ideologically aligned with major bilateral donors.*
  - *Hypothesis #2b: The volume of governance aid channeled through state actors increases more when the recipient has high State fiscal capacity.*

Data and Method

Bilateral aid data

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[3]. 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.

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

Providers that report to the OECD include both DAC and non-DAC country members, multilateral institutions, as well as private philanthropic foundations[4]. 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[5]. 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 the Top 20 largest bilateral providers (see Table 3 in the *Appendix*). Restricting the sample to country with complete data resulted in the inclusion of 119 recipients in the final sample.

I classify aid flows into two categories based on the channel of delivery: (1) state and (2) non-state. This classification highlights the key difference between government-led and "bypass" aid (Dietrich 2013). The channel of delivery is the first implementing partner. It is the entity that is directly accountable to the agency providing the funds for implementing them. Both parties are normally linked by a contract or another binding agreement[6]. 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 (MDBs). Non-official actors include Non-Governmental Organizations (NGOs) and private companies[7]. During the period from 2005 to 2015, approximately one quarter of all commitments were carried out by non-state actors (See Figure 6).

The channel of delivery became an optional reporting item on the new CRS++ reporting scheme in 2004 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 through which the project is implemented. Moreover, for 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 Imputation methodology in the Appendix).

[4]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.

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

[6]In the case of loans, the borrower is reported as the first implementing partner, as it is the first entity outside the donor country that receives the funds.

[7]In the heterogeneity section below, I examine subgroup variation within non-state channels.

Disasters and weather data

Climate-related disasters vary widely in type and intensity. Focusing on event occurrence alone ignores this heterogeneity, yet socioeconomic loss-based severity measures risk endogeneity bias (Kahn 2005; Toya and Skidmore 2007; Jones, Guha-Sapir, and Tubeuf 2022). To address these limitations, I construct a physical mesure of exposure to multi-hazard intensity, following 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.

Disasters

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*.

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.

Weather

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).

Population

Finally, to account for population exposure, I integrate high-resolution population counts from the Landscan dataset (Bright and Coleman, n.d.), which provides spatial granularity at approximately 1 km^2. The exposure measure is defined as the interaction between hazard occurrence and the population exposed.

Other data

I use several variables from the V-Dem database, version 14 (Michael Coppedge et al., n.d.). First, to proxy the recipient's internal discipline: (i) the Regimes of the World measure (*v2x_regime*), the civil society participation index (*v2x_cspart*), the judicial constraints on the executive index (*v2x_jucon*), and the legislative constraints on the executive index (*v2xlg_legcon*). Second, to measure the recipient government's fiscal capacity, I use the State Fiscal Capacity index (*v2stfisccap*)[8]. To complete data on the recipient's internal discipline, I also use data on the death rate of internal conflicts from the Uppsala Conflict Data Program (Sundberg and Melander 2013), defined as the deaths of combatants and civilians due to fighting, per 100,000 people.

I use ideal point estimates based on voting behavior in the United Nations General Assembly compiled by (Fjelstul, Hug, and Kilby 2025). Contrary to previous versions of the dataset, the ideal point estimates are based on years rather than UNGA sessions. My alignment measure is based on the average proportion of votes in the UNGA for which the recipient country and the Group of 7 (G7)[9] voted in the same way (either yes, no or abstention). The measure is calculated for each year and then averaged across all G7 donors to determine the recipient's alignment.

Multi-hazard exposure measures

Grid-level—I first crop grid-level weather data to the boundaries of each ADM-1 region in GEODIS. From this subset, I derive daily climate indices for each weather parameter (see Table 1). Yearly, hazard-specific intensity measures are then constructed based on deviations of these daily indices from their historical norms, an approach grounded in both climate science (Zhang et al. 2011; IPCC 2021) and climate econometrics (e.g., S. Hsiang 2016). Specifically, I calculate

[8] As a robustness check, I employ data from the IMF's *World Revenue Longitudinal Database* (WoRLD) (Mansour 2025), which provides standardized tax and non-tax revenue data (1990–2022) for 190 countries. However, missing observations, particularly for lower-income countries with weak institutional settings, reduce the effective sample size. This motivate the decision to use V-Dem's State Fiscal Capacity index in the main analysis.

[9] The G7 consists of Canada, France, Germany, Italy, Japan, the United Kingdom and the United States.

Table 1: Hazard indices

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

the annual count of days exceeding a 95th-percentile threshold, relative to a 1980–2000 baseline[10].

This relative measure captures the intuition that a higher frequency of extreme daily events increases the likelihood of socioeconomic damages and subsequent disaster declaration. A key strength of this method is that it enables direct aggregation and comparison across diverse climate hazards by standardising intensity in terms of "extreme" days. Figure 1 shows that these physical exposure measures are consistent with the timing of disasters. On average, the value of the measure reaches its maximum in the same year that the disaster occurs.

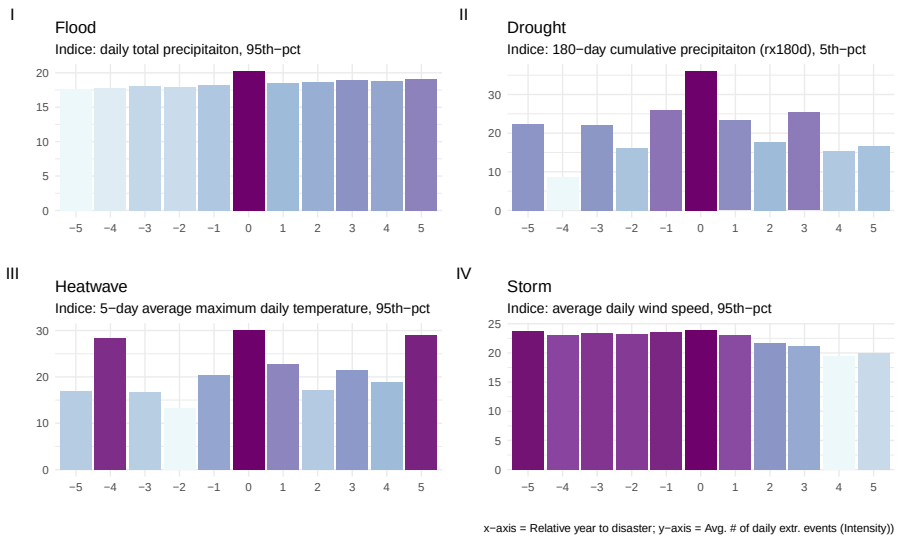


Figure 1: Average hazard intensity and relative to disaster year (ADM-1 level)

ADM-level—The spatial extent of disaster events varies widely. Besides, expo-

[10] *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).

sure could simply increase with country size. To account for this, I follow two approaches. In the main specifications, I calculate the population density within each affected adminstrative units, then normalize it by the overall country population density. In alternative specifications, I normalize the measures by taking the ratio of the population count in the affected administrative units to the total population in the countries. As past disasters could affect current exposure, I use population data for the year 2000, the first year of the observation sample.

Country-level—Because my outcome variables are at the country-year level, I need to aggregate event-level physical exposure measures to the same level of analysis. Since damages accumulate, I achieve aggregation through summation. This approach consider the cumulative effect which may derive from the occurrence of multiple events in the same time period. As robustness checks, I also consider the maximum physical measure experienced throughout all events in a given year (as in S. M. Hsiang and Narita (2012)).

This approach assumes a linear relationship between exposure and damages. Yet, empirical evidence suggests the true relationship is nonlinear and convex. Standard approaches to modeling exposure impacts rely on damage functions, which are inherently scale-, location-, and time-dependent. Given the impracticality of estimating bespoke functions for every event in my sample, I adopt a widely used parametric form: squaring the physical exposure measure to reflect the concave, upward-sloping relationship observed in empirical damage functions. For robustness, I extend the analysis to higher-order terms (cube and quartic powers) following (Coronese 2025).

The exposure measure for recipient country r in year t, denoted $E_{r,t}$, is aggregated from individual disaster events $d_{j,r,t}$ using the sum function:

$$E_{r,t} = \sum_{j=1}^{d_{r,t}} s_{j,r,t}^2$$

where $s_{j,r,t}$ is the disaster event-specific exposure measure for event $d_{j,r,t}$.

Figure 7 presents a correlation matrix comparing alternative hazard severity measures. As expected, the highest correlations appear among measures using similar exposure metrics (based on population density or population count). The matrix also reveals cross-metric correlations, suggesting that different exposure operationalizations capture overlapping dimensions of disaster risk. When comparing these measures to EM-DAT's estimated number of people affected, a standard proxy for socioeconomic impact, the results show low correlation for density-based metrics but moderate correlation for count-based measures.

Table 2 presents summary statistics for all variables included in the empirical analysis.

Table 2: Descriptive Table

Variables	Min.	p25	Med.	Mean	p75	Max.
Outcomes (ODA Commit., thousand USD)						
Overall	0.00	0.00	0.00	19.85	2.65	14457.75
State	*0.00*	*0.00*	*0.00*	*11.83*	*0.21*	*8120.29*
Non-State	*0.00*	*0.00*	*0.00*	*4.83*	*0.59*	*6320.26*
Development	0.00	0.00	0.00	13.00	0.55	10467.63
State	*0.00*	*0.00*	*0.00*	*8.78*	*0.01*	*6792.08*
Non-State	*0.00*	*0.00*	*0.00*	*2.14*	*0.00*	*3687.95*
Governance	0.00	0.00	0.00	2.42	0.05	3541.13
State	*0.00*	*0.00*	*0.00*	*1.31*	*0.00*	*2654.81*
Non-State	*0.00*	*0.00*	*0.00*	*0.59*	*0.00*	*2306.19*
Humanitarian	0.00	0.00	0.00	1.90	0.00	1401.00
State	*0.00*	*0.00*	*0.00*	*0.09*	*0.00*	*394.34*
Non-State	*0.00*	*0.00*	*0.00*	*1.68*	*0.00*	*1396.97*
Other	0.00	0.00	0.00	0.09	0.00	340.58
State	*0.00*	*0.00*	*0.00*	*0.05*	*0.00*	*340.58*
Non-State	*0.00*	*0.00*	*0.00*	*0.02*	*0.00*	*38.82*
Treatments (Disasters)						
Occurence (Dummy)	0.00	0.00	1.00	0.53	1.00	1.00
Intensity (Cont.)	0.00	0.00	0.01	0.42	0.23	5.71
Other variables						
Recip. domestic politics						
Regime Type (Row)	0.00	1.00	1.00	1.32	2.00	3.00
Constraints on the Executive	0.02	0.25	0.51	0.50	0.75	0.97
Civil Society Participation	0.02	0.47	0.68	0.62	0.79	0.96
Internal Conflict (Dummy)	0.00	0.00	0.00	0.29	1.00	1.00
Intern. Conflict Intensity	0.00	0.00	0.00	3.05	0.07	2224.09
Recip. alternative finance						
State Fiscal Capacity	-2.79	-0.23	0.58	0.57	1.42	2.57
% Multilateral ODA	0.00	6.50	20.36	24.40	38.73	90.63
Recip. diplomatic alignment						
UN Alignment (G7)	0.40	1.61	1.89	1.86	2.11	3.50

Empirical strategy

This study estimates the dynamic causal effect of climate-related disaster exposure on channel-specific Official Development Assistance (ODA) flows (Y_{drt}), where Y_{drt} represents aid from donor d to recipient r in year t. The analysis employs a generalized event-study design with staggered treatment (Schmidheiny and Siegloch 2023), where treatment is defined as the occurrence of at least one disaster event in recipient r, scaled by the magnitude of exposure. The generalized event-study design is especially relevant in the case of multiple treatments per unit.

The baseline specification models the relationship between disaster exposure and ODA flows using a two-way fixed effects (TWFE) framework with binned endpoints:

$$Y_{drt} = \alpha_{dr} + \tau_t + \sum_{j=\underline{j}}^{\bar{j}} \beta_j \mathbb{D}^j_{rt} + \sum_{z \in Z} \beta_z X_{zdrt} + \epsilon_{drt} \tag{1}$$

where:

- Y_{drt} is the dependent variable (channel-specific ODA flows).
- $D^j_{r,t}$ is the treatment variable, capturing leads and lags of disaster exposure faced by recipient country r at year t, defined as:

$$D^j_{r,t} = \begin{cases} \sum_{s=-\infty}^{-3} d_{r,t-s} & \text{if } k = -3 \\ d_{r,t-j} & \text{if } -3 < k < 5 \\ \sum_{s=5}^{\infty} d_{r,t-s} & \text{if } k = 5 \end{cases}$$

This specification includes donor×recipient pair fixed effects (α_{dr}) to absorb time-invariant heterogeneity in bilateral aid relationships, year fixed effects (τ_t) to control for global shocks, and recipient-specific linear time trends to account for slow-moving confounders. The effect window spans from three years before to five years after disaster occurrence ($J = [-3, 5]$), consistent with existing literature on disaster response dynamics. Standard errors are clustered at the recipient-country level to address serial correlation.

A key constraint of this staggered design is the requirement to observe treatment status over a longer period than the outcome variable. With treatment data available from 2000 to 2018, the effective sample period for the dependent variable is restricted to 2005–2015.

The estimand of interest is a semi-elasticity, representing the percentage change in ODA flows associated with disaster exposure. Given the non-negative and

non-normal distribution of ODA data[11] (see Figure 8), I employ a Poisson Pseudo-Maximum Likelihood (PPML) estimator (Silva and Tenreyro 2006), which avoids the biases associated with log-transformations in the presence of heteroskedasticity and zero-valued observations (Head and Mayer 2014; Mullahy and Norton 2024). The PPML approach estimates the average percentage change in the outcome rather than the change in the average outcome, aligning with the Ratio-of-Ratios (RoR) interpretation of treatment effects (Moreau-Kastler 2025). This contrasts with conventional two-way fixed effects log-OLS estimators, which target individual log-point changes and may be biased in staggered settings with heterogeneous treatment effects (Chen and Roth 2024)[12].

For causal interpretation of the estimated coefficients (β_j), I rely on three core identifying assumptions. First, the strict exogeneity assumption posits that, conditional on observables and time-invariant unobservables, treatment assignment is effectively random. Second, the parallel trends assumption requires that, in the absence of treatment, the outcomes of treated and untreated units would have evolved similarly over time. Third, I assume no systematic anticipation of disaster events by donors or recipients. The plausibility of these assumptions is supported by empirical tests: small and statistically insignificant pretreatment coefficients in the event study design suggest the absence of diverging pre-trends that would violate the parallel trends assumption, while the lack of systematic pre-treatment divergence in ODA flows mitigates concerns about reverse causality.

To further strengthen identification, the empirical strategy incorporates several robustness features. Donor-recipient fixed effects eliminate time-invariant attributes of bilateral relationships, while year fixed effects control for common shocks that might simultaneously affect aid flows and disaster probability. Recipient-specific linear time trends account for gradual changes in unobserved confounders. The analysis also leverages quasi-random variation in disaster intensity, which helps address concerns about treatment homogeneity and reduces bias from unobserved time-varying confounders (Noy 2009; Sun and Abraham 2021; Cavallo et al. 2013). Physical measures of disaster intensity are particularly valuable in this context, as they provide exogenous variation less susceptible to endogeneity concerns (Felbermayr and Gröschl 2014; Felbermayr et al. 2022; Botzen, Deschenes, and Sanders 2019).

The staggered treatment framework also presents two additional identification challenges: carryover effects from dynamic treatment responses and non-absorbing treatments where units experience multiple disaster events (see Fig-

[11] 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).

[12] 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.

ure 9). Donor responses to disasters often materialize with significant lags due to coordination requirements for reconstruction efforts, creating potential bias if current treatments influence future outcomes. To address these issues, I adopt a non-parametric event-study design with binned endpoints and distributed lags (Schmidheiny and Siegloch 2023), which makes the additional assumption that dynamic treatment effects stabilize outside the specified window. The empirical relevance of these concerns is evident in the data, as most recipient countries experience multiple disaster events during the sample period (Figure 9).

Despite these safeguards, several limitations remain. Fixed effects models do not fully eliminate bias from unobserved time-varying confounders that might simultaneously affect disaster occurrence and aid flows. The assumption of treatment homogeneity may not hold across all disaster types and intensities, and the effect stabilization assumption could be violated in cases of protracted crises. Moreover, residual confounding from other time-varying factors cannot be entirely ruled out. These caveats are addressed through robustness checks, including alternative model specifications and sensitivity analyses.

Results

Baseline results

Figure 2 presents the baseline event study estimates for commitments delivered through non-state and state channels. Across both specifications, the coefficients for the leads are statistically non-significant, which lends empirical support to the parallel trends assumption. This suggests that aid flows are not driven by anticipatory effects or pre-existing trends.

Following the disaster, the effect on state-led commitments is negative but not significant. This remains the case despite a spike in year two. In contrast, aid channelled through non-state actors exhibits an immediate and statistically significant hike of approximately 5.7% for each standard deviation increase in disaster intensity. Estimates remain positive in subsequent periods, albeit not statistically significant, until year 4, when the estimate reaches its maximum and becomes significant.

These results suggest a "bypass" phenomenon in the immediate response to climate-related disasters, whereby donors systematically pivot away from government-to-government channels in favour of non-state intermediaries. In the immediate aftermath, non-state commitments appear to replace state commitments. In the medium term, an increase in non-state commitments alone suggests an growing proportion of non-state channels in total commitments.

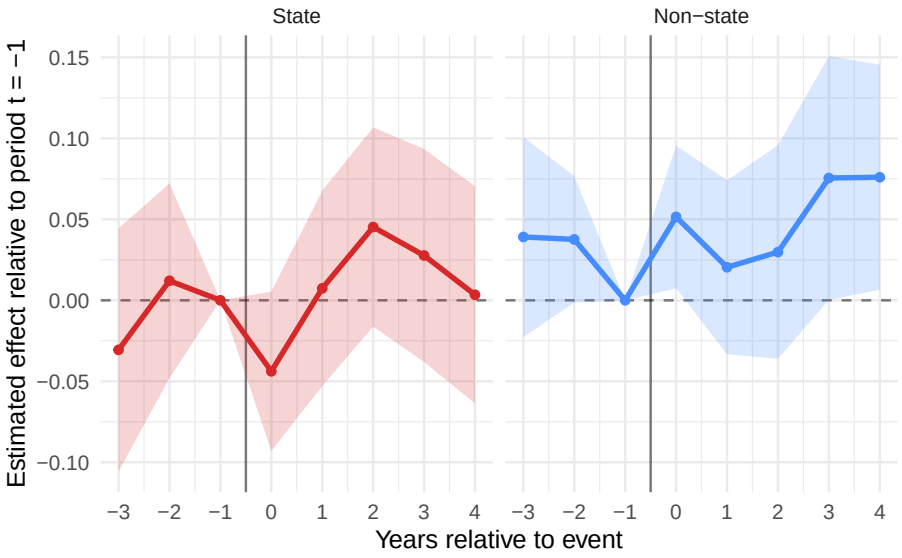


Figure 2: Point estimates and corresponding 95% confidence intervals for one pooled standard deviation of the exposure measure, on state-channeled (red) and non-state-channeled (blue) total deflated commitments in million USD, as estimated by the baseline model, using a PPML estimator. The number of leads considered is f = 3 and the number of lags is l = 5, with binned endpoints. The regressions include provider-recipient and provider-year fixed effects, as well as recipient-specific time-varying slopes and region-year fixed effects. The effect at the pre-event period is normalized to zero. Standard errors are clustered at the recipient level. The corresponding regression coefficients are provided in Table 6 in the Appendix.

Extensive margin

Due to the large numnber of zeroes in the outcomes, it is important to consider how the exposure to disasters impacts aid flows at the extensive margin. Figure 3 presents the estimates for binary outcomes. The outcomes takes equals 1 when there is a positive dyadic commitment value at year t, and zero otherwise.

The results show a positive and significant effect on commitments delivered through non-state channels in the aftermath of the shock, while the effect remains non-significant for state-led commitments. This suggests that the emergency responses observed immediately after the shock are driven by new bilateral aid flows committed following the shock. The extensive margin effect is not significant in the medium term, implying that the positive effect observed in year 4 for both margins is due to existing aid relationships between providers and recipient countries.

These results also confirm the choice to use non-linear estimators to account for the large mass at zero in the outcome variable.

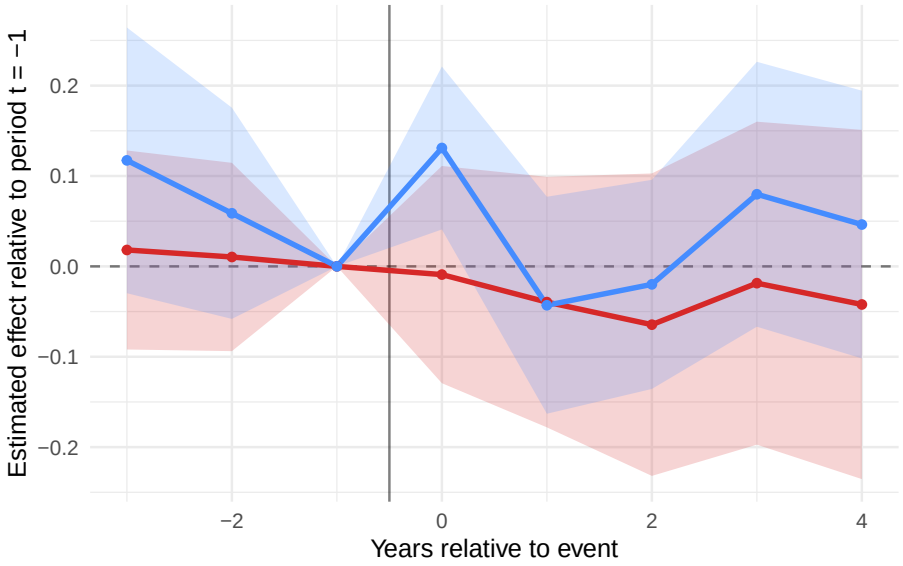


Figure 3: Event study estimates of a one pooled standard-deviation increase in exposure on the extensive margin of bilateral aid, by delivery channel (state: red; non-state: blue). Point estimates and 95% confidence intervals from a logistic regresssion model using the GLM function. The specification includes 3 leads and 5 lags with binned endpoints, provider-recipient and provider-year fixed effects, recipient-specific time-varying slopes, and region-year fixed effects. Pre-event effects are normalized to zero. Standard errors are clustered at the recipient level. Regression coefficients are reported in Appendix, Table 7.

Sensitivity checks

To assess the robustness of my findings, I implement a series of sensitivity checks. First, I test alternative fixed effects specifications to account for unobserved heterogeneity at different levels of aggregation (Table Table 8). Second, I exclude the largest bilateral donor, the United States, from the sample to evaluate whether the results are driven by its influence on total aid flows (Table Table 9). Finally, I employ alternative measures of hazard exposure to ensure that my findings are not contingent on a specific operationalization of disaster risk (Table Table 10).

Heterogeneity

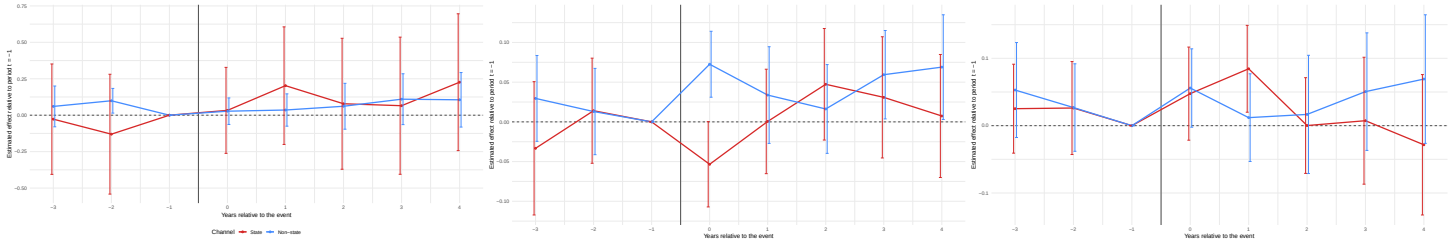
Intervention type

There is heterogeneity in the use of delivery channels across sectors (Table 11). Most humanitarian aid is implemented by non-state actors (88.6%). While a majority of development and governance activities are implemented by state actors, non-state actors still represent 16.5% and 24.4% of total commitments in these areas, respectively.

The main effect of the shock on bilateral aid is primarily driven by development-focused activities, with a spike in the immediate aftermath and sustained medium-term increases. The effects for state and non-state channels exhibit opposing dynamic trends, suggesting a substitution effect between channels of delivery for development-focused activities. This divergence implies that recipients may reallocate their commitments across channels in response to the shock, prioritizing non-state intermediairies in the short term.

Both state and non-state channels show a contemporaneous, though statistically insignificant, increase in commitments. In the subsequent year, the non-state effect diminishes in amplitude, while the state effect becomes positive and significant. Over time, the state-led effect tapers off, whereas the non-state effect appears to rebound. This pattern may reflect differential strategic use of governance-focused activities.

Neither state nor non-state channels exhibit significant effects on humanitarian commitments. This null result aligns with the dominant role of multilateral actors in emergency aid provision, which likely insulates bilateral commitments (state and non-state) from short-term shocks.



(a) Humanitarian **(b)** Development **(c)** Governance

Figure 4: Point estimates and corresponding 95% confidence intervals for one pooled standard deviation of the exposure measure, on state-channeled (red) and non-state-channeled (blue) total deflated commitments in million USD, as estimated by the baseline model, using a PPML estimator. The number of leads considered is f = 3 and the number of lags is l = 5, with binned endpoints. The regressions include provider-recipient and provider-year fixed effects, as well as recipient-specific time-varying slopes and region-year fixed effects. The effect at the pre-event period is normalized to zero. Standard errors are clustered at the recipient level. The corresponding regression coefficients are provided in Table 7 in the Appendix.

- Large disaster events
- Disbursements
- Official (Multilaterals) vs. Non-Official (Private sector) non-State channels
- Statist/Market-oriented donors (Dietrich 2021)

Mechanisms

Domestic politics

- Political regimes
- Executive constraints (judicial and legislative)
- Civil society participation
- Internal conflicts

Alternative public finance sources

- State fiscal capacity
- Multilateral ODA (% country "aid market")
- China public finance

Political alignment

- Alignment with G7 in UNGA votes

Conclusion

This study examines how climate-related disasters reshape foreign aid allocation across delivery channels. Using dyadic panel data on bilateral aid flows over the period 2005-2015 with a generalized event study approach, I find three main results. First, climate disasters trigger a significant increase in development aid channeled through non-state actors, consistent with donors seeking rapid deployment and reduced fiduciary risk in post-disaster environments. Second, this shift partially substitutes for state-channeled aid in the immediate aftermath, suggesting donors perceive a trade-off between speed and state ownership during crises. Third, governance-targeted aid to state institutions increases following disasters, indicating that donors pursue a dual strategy: bypassing the state for

immediate service delivery while simultaneously investing in institutional capacity for long-term resilience. Notably, I find no significant increase in bilateral humanitarian aid following disasters. This null result suggests persistent coordination failures in emergency financing, potentially reflecting free-rider behavior among bilateral donors who may defer to multilateral mechanisms or non-official aid providers. Taken together, these patterns reveal a post-disaster aid bargaining agreement in which donors strategically diversify across intervention types and delivery channels to balance competing objectives. From the recipient's perspective, this combination represents a second-best option: governments accept the loss of control attached to bypass aid in exchange for immediate liquidity and governance support, which postpones the need for more costly domestic reforms.

Appendix

Table 3: List of donor sample

Rank	Name	Cum. % of total bilateral commit.
1	United States	30.38
2	EU Institutions	44.96
3	Japan	57.09
4	Germany	66.60
5	France	74.15
6	United Kingdom	79.49
7	Australia	82.03
8	Canada	84.39
9	Netherlands	86.50
10	Spain	88.33
11	Norway	90.04
12	Korea	91.58
13	Sweden	93.00
14	Italy	94.42
15	Switzerland	95.76
16	Belgium	97.04
17	Denmark	98.26
18	Austria	98.95
19	Finland	99.49
20	Ireland	100.00

Table 4: List of recipient countries

Name	USD	Rank	% total commit.
Afghanistan	62298.15630	2	6.98
Albania	3419.95428	61	0.38
Algeria	2363.85025	74	0.26
Angola	2543.88800	71	0.28
Argentina	1057.59604	93	0.12
Armenia	3438.03190	60	0.39
Azerbaijan	1983.33348	79	0.22
Bangladesh	18203.40900	12	2.04
Barbados	72.44360	117	0.01
Benin	4742.67151	53	0.53
Bhutan	489.56455	106	0.05

(continued)

Name	USD	Rank	% total commit.
Bolivia	5877.14920	45	0.66
Bosnia and Herzegovina	5665.53327	46	0.63
Botswana	2289.15017	75	0.26
Brazil	8541.36559	31	0.96
Burkina Faso	7047.05750	39	0.79
Burundi	4092.11579	56	0.46
Cabo Verde	1136.43290	90	0.13
Cambodia	6629.19194	42	0.74
Cameroon	9164.40873	30	1.03
Central African Republic	2561.21406	70	0.29
Chad	4862.82683	52	0.54
Chile	1450.11026	84	0.16
China (People's Republic of)	15685.99741	16	1.76
Colombia	13997.14052	19	1.57
Comoros	355.43397	110	0.04
Congo	4936.49493	50	0.55
Costa Rica	884.28567	97	0.10
Croatia	1607.19927	83	0.18
Cuba	1029.01670	94	0.12
Côte d'Ivoire	9578.00085	28	1.07
Democratic People's Republic of Korea	782.26098	100	0.09
Democratic Republic of the Congo	22175.06315	10	2.48
Djibouti	1060.58845	92	0.12
Dominican Republic	2789.19252	66	0.31
Ecuador	3230.57615	63	0.36
Egypt	16808.35721	15	1.88
El Salvador	3718.29336	59	0.42
Equatorial Guinea	238.55663	113	0.03
Eritrea	841.15209	99	0.09
Eswatini	877.36148	98	0.10
Ethiopia	24188.02717	9	2.71
Fiji	601.63967	103	0.07
Gabon	970.70508	96	0.11
Gambia	491.17154	105	0.06
Georgia	6705.76716	41	0.75
Ghana	11516.36415	25	1.29
Guatemala	4608.82123	55	0.52
Guinea	2382.43877	72	0.27
Guinea-Bissau	571.77834	104	0.06
Guyana	1101.55052	91	0.12

(continued)

Name	USD	Rank	% total commit.
Haiti	12795.45914	22	1.43
Honduras	4874.44337	51	0.55
India	36592.92530	3	4.10
Indonesia	28338.86830	5	3.17
Iran	443.44954	108	0.05
Iraq	73395.89904	1	8.22
Jamaica	1166.39689	88	0.13
Jordan	14829.65361	17	1.66
Kazakhstan	1411.85099	86	0.16
Kenya	22169.05286	11	2.48
Kyrgyzstan	2381.37188	73	0.27
Lao People's Democratic Republic	3048.34704	64	0.34
Lebanon	7475.76358	38	0.84
Lesotho	1653.99236	82	0.19
Liberia	7598.07718	36	0.85
Libya	1159.25572	89	0.13
Madagascar	4955.07979	49	0.55
Malawi	8045.60188	34	0.90
Malaysia	1175.19096	87	0.13
Maldives	259.32135	112	0.03
Mali	10690.28714	26	1.20
Mauritania	1979.93245	80	0.22
Mauritius	1696.97525	81	0.19
Mexico	7503.22200	37	0.84
Mongolia	3300.33205	62	0.37
Morocco	17592.30369	14	1.97
Mozambique	17978.36952	13	2.01
Myanmar	11910.74880	24	1.33
Namibia	2883.22654	65	0.32
Nepal	6599.65558	43	0.74
Nicaragua	4631.08526	54	0.52
Niger	5388.12014	47	0.60
Nigeria	30756.98586	4	3.44
North Macedonia	2788.33816	67	0.31
Oman	71.45857	118	0.01
Pakistan	25823.03991	8	2.89
Panama	612.78961	102	0.07
Paraguay	1448.39817	85	0.16
Philippines	13749.96670	20	1.54
Rwanda	6947.35697	40	0.78

(continued)

Name	USD	Rank	% total commit.
Sao Tome and Principe	148.15285	116	0.02
Saudi Arabia	23.46717	119	0.00
Senegal	8481.17973	32	0.95
Serbia	13000.30523	21	1.46
Seychelles	189.86718	114	0.02
Sierra Leone	3900.76499	58	0.44
Solomon Islands	2582.60469	69	0.29
Somalia	7665.22203	35	0.86
South Africa	14264.24470	18	1.60
Sri Lanka	8128.36248	33	0.91
Suriname	716.49219	101	0.08
Syrian Arab Republic	9440.82065	29	1.06
Tajikistan	2219.63902	77	0.25
Thailand	3987.54359	57	0.45
Timor-Leste	2277.50041	76	0.26
Togo	2068.88327	78	0.23
Trinidad and Tobago	148.17249	115	0.02
Tunisia	9851.97731	27	1.10
Turkmenistan	266.25878	111	0.03
Türkiye	28026.53334	6	3.14
Uruguay	444.48867	107	0.05
Uzbekistan	2667.48614	68	0.30
Vanuatu	1011.35154	95	0.11
Venezuela	369.73408	109	0.04
Viet Nam	25904.31646	7	2.90
Yemen	5150.51531	48	0.58
Zambia	11945.26873	23	1.34
Zimbabwe	6285.78274	44	0.70

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:

Reported name	Amount (USD)	Percent.
Missing Channel Code		
Yes	98001.18	87.5%
No	14012.06	12.5%
'Other' Channel (90000)		
Yes	12698.89	9.2%
No	126003.11	90.8%

`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)[13].

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.

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[14].

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

[13]The Excel file can be found here.

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

Table 5

sector_name	sector_code	total_amount	na_amount	share_na	cumsum
VII. Action Relating to Debt	600	67856.3	22953.104	0.2015780	20
I.5.a. Government & Civil Society-general	151	191493.5	14490.842	0.1272610	33
II.1. Transport & Storage	210	203246.4	11064.024	0.0971661	43
III.1.a. Agriculture	311	100628.7	7543.285	0.0662464	49
I.4. Water Supply & Sanitation	140	113686.6	7143.127	0.0627321	55

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

as an activity delivered through state or non-state channels. In the robustness section, I conduct the analysis excluding actions relating to debt.

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

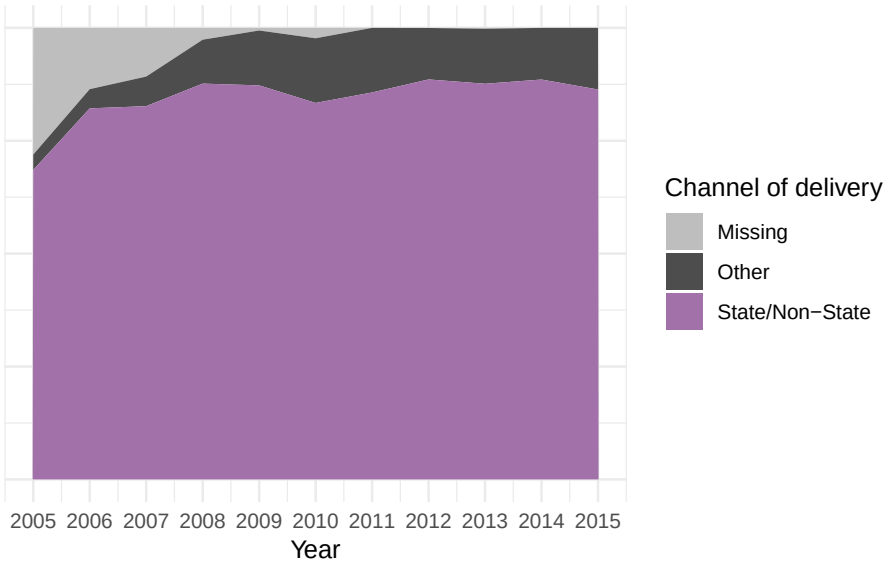


Figure 5: Missing data in channel of delivery (after imputation)

Coefficient tables

Table 6: See Figure 2

Dependent Variable:	Bilateral aid	
	State channels	Non-State channels
Model:	(1)	(2)
Variables		
≤ -3	-0.0306	0.0391
	(0.0383)	(0.0315)
-2	0.0121	0.0376*
	(0.0307)	(0.0199)
0	-0.0438*	0.0515**
	(0.0251)	(0.0225)
1	0.0074	0.0204
	(0.0307)	(0.0274)
2	0.0452	0.0298
	(0.0314)	(0.0336)
3	0.0277	0.0755**
	(0.0335)	(0.0384)
≥ 4	0.0034	0.0760**
	(0.0342)	(0.0355)
Fixed-effects		
Provider × Recipient	Yes	Yes
Provider × Year	Yes	Yes
Recipient	Yes	Yes
Region × Year	Yes	Yes
Varying Slopes		
t (Recipient)	Yes	Yes
Fit statistics		
Observations	23,416	24,963
Squared Correlation	0.80372	0.94188
Pseudo R^2	0.83960	0.87508
BIC	460,612.6	174,666.5

Clustered (Recipient) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: See Figure 3

Dependent Variable:	Bilateral aid	
	State channels	Non-State channels
Model:	(1)	(2)
Variables		
≤ -3	-0.0336	0.0237
	(0.0378)	(0.0343)
-2	0.0095	0.0346
	(0.0299)	(0.0216)
0	-0.0419*	0.0573**
	(0.0248)	(0.0237)
1	0.0090	0.0296
	(0.0309)	(0.0300)
2	0.0463	0.0408
	(0.0321)	(0.0396)
3	0.0293	0.0869**
	(0.0335)	(0.0442)
≥ 4	0.0077	0.0911**
	(0.0343)	(0.0437)
Fixed-effects		
Provider × Recipient	Yes	Yes
Provider × Year	Yes	Yes
Recipient	Yes	Yes
Region × Year	Yes	Yes
Varying Slopes		
t (Recipient)	Yes	Yes
Fit statistics		
Observations	26,146	27,066
Squared Correlation	0.79985	0.93343
Pseudo R^2	0.84116	0.87528
BIC	484,137.5	185,035.8

Clustered (Recipient) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8: Sensitivity check: alternative fixed effects structure

Dependent Variable:	Bilateral aid					
	State channels	Non-State channels	State channels	Non-State channels	State channels	Non-State channels
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
≤ -3	0.0130	0.0656*	-0.0358	-0.0308	-0.0397	0.0492
	(0.0268)	(0.0398)	(0.0366)	(0.0511)	(0.0414)	(0.0323)
-2	-0.0027	0.0164	0.0044	0.0116	0.0013	0.0512**
	(0.0305)	(0.0216)	(0.0368)	(0.0343)	(0.0357)	(0.0200)
0	-0.0541**	0.0731**	-0.0544**	0.0777**	-0.0457*	0.0605**
	(0.0271)	(0.0288)	(0.0269)	(0.0340)	(0.0274)	(0.0240)
1	0.0182	0.0101	0.0089	0.0562	0.0055	0.0247
	(0.0371)	(0.0423)	(0.0354)	(0.0419)	(0.0332)	(0.0288)
2	0.0582*	0.0249	0.0529**	0.0697	0.0455	0.0287
	(0.0311)	(0.0398)	(0.0229)	(0.0606)	(0.0332)	(0.0353)
3	0.0339	0.0856*	0.0219	0.1142*	0.0237	0.0859**
	(0.0313)	(0.0471)	(0.0311)	(0.0628)	(0.0367)	(0.0388)
≥ 4	0.0457	0.0520	0.0165	0.1014	0.0015	0.0738**
	(0.0331)	(0.0569)	(0.0303)	(0.0649)	(0.0370)	(0.0355)
Fixed-effects						
Provider × Recipient	Yes	Yes	Yes	Yes	Yes	Yes
Provider × Year	Yes	Yes	Yes	Yes	Yes	Yes
Recipient			Yes	Yes	Yes	Yes
Region × Year					Yes	Yes
Varying Slopes						
t (Recipient)			Yes	Yes	Yes	Yes
Fit statistics						
Observations	22,201	23,682	22,201	23,682	22,201	23,682
Squared Correlation	0.60618	0.54152	0.75048	0.87791	0.81002	0.94431
Pseudo R^2	0.79802	0.81531	0.83438	0.85673	0.84254	0.87041
BIC	546,111.5	217,694.5	454,240.6	176,650.1	434,057.4	163,289.3

Clustered (Recipient) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figures

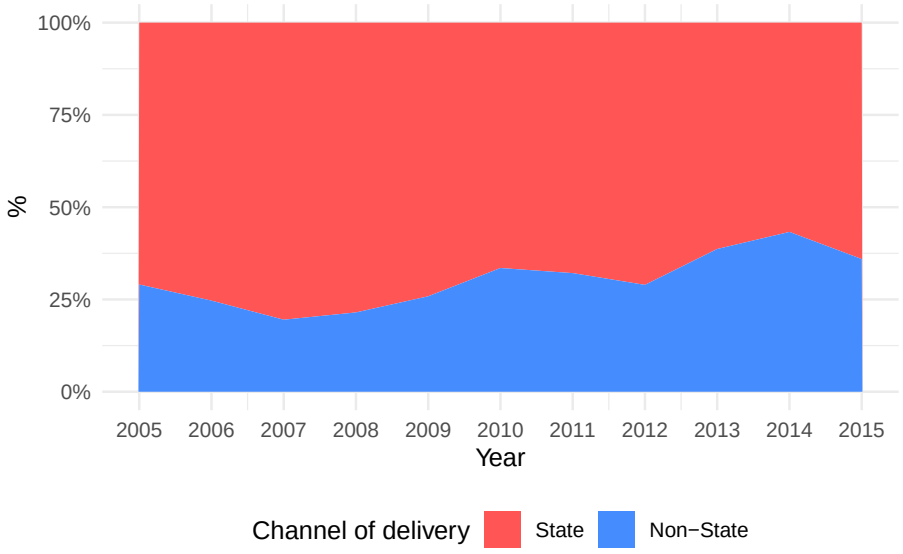


Figure 6: Share of commitments by channel of delivery

Table 9: Sensitivity check: donor sample without the United States

Dependent Variable:	Bilateral aid	
	State channels	Non-State channels
Model:	(1)	(2)
Variables		
≤ -3	-0.0571	0.0602*
	(0.0348)	(0.0325)
-2	-0.0219	0.0393
	(0.0389)	(0.0255)
0	-0.0548*	0.0782***
	(0.0281)	(0.0299)
1	-0.0076	0.0448
	(0.0339)	(0.0427)
2	0.0412	0.0348
	(0.0337)	(0.0392)
3	0.0294	0.0924**
	(0.0347)	(0.0452)
≥ 4	0.0042	0.0870*
	(0.0362)	(0.0475)
Fixed-effects		
Provider × Recipient	Yes	Yes
Provider × Year	Yes	Yes
Recipient	Yes	Yes
Region × Year	Yes	Yes
Varying Slopes		
t (Recipient)	Yes	Yes
Fit statistics		
Observations	20,892	22,373
Squared Correlation	0.80710	0.88303
Pseudo R^2	0.83919	0.78334
BIC	360,705.3	136,365.8

Clustered (Recipient) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10: Sensitivity check: alternative hazard exposure measure (weighted by population counts)

Dependent Variable:	Bilateral aid	
	State channels	Non-State channels
Model:	(1)	(2)
Variables		
≤ -3	-0.0397	0.0492
	(0.0414)	(0.0323)
-2	0.0013	0.0512**
	(0.0357)	(0.0200)
0	-0.0457*	0.0605**
	(0.0274)	(0.0240)
1	0.0055	0.0247
	(0.0332)	(0.0288)
2	0.0455	0.0287
	(0.0332)	(0.0353)
3	0.0237	0.0859**
	(0.0367)	(0.0388)
≥ 4	0.0015	0.0738**
	(0.0370)	(0.0355)
Fixed-effects		
Provider × Recipient	Yes	Yes
Provider × Year	Yes	Yes
Recipient	Yes	Yes
Region × Year	Yes	Yes
Varying Slopes		
t (Recipient)	Yes	Yes
Fit statistics		
Observations	22,201	23,682
Squared Correlation	0.81002	0.94431
Pseudo R^2	0.84254	0.87041
BIC	434,057.4	163,289.3

Clustered (Recipient) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 11: Main sectors by channel of delivery, in % total commitments, 2005-15

	Channel			
	state	non-state	other	Total
Development	67.5	16.5	16.0	100
Governance	54.2	24.4	21.4	100
Humanitarian	4.7	88.6	6.7	100
Other	55.2	24.3	20.5	100
Ensemble	**58.7**	**25.5**	**15.8**	**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.

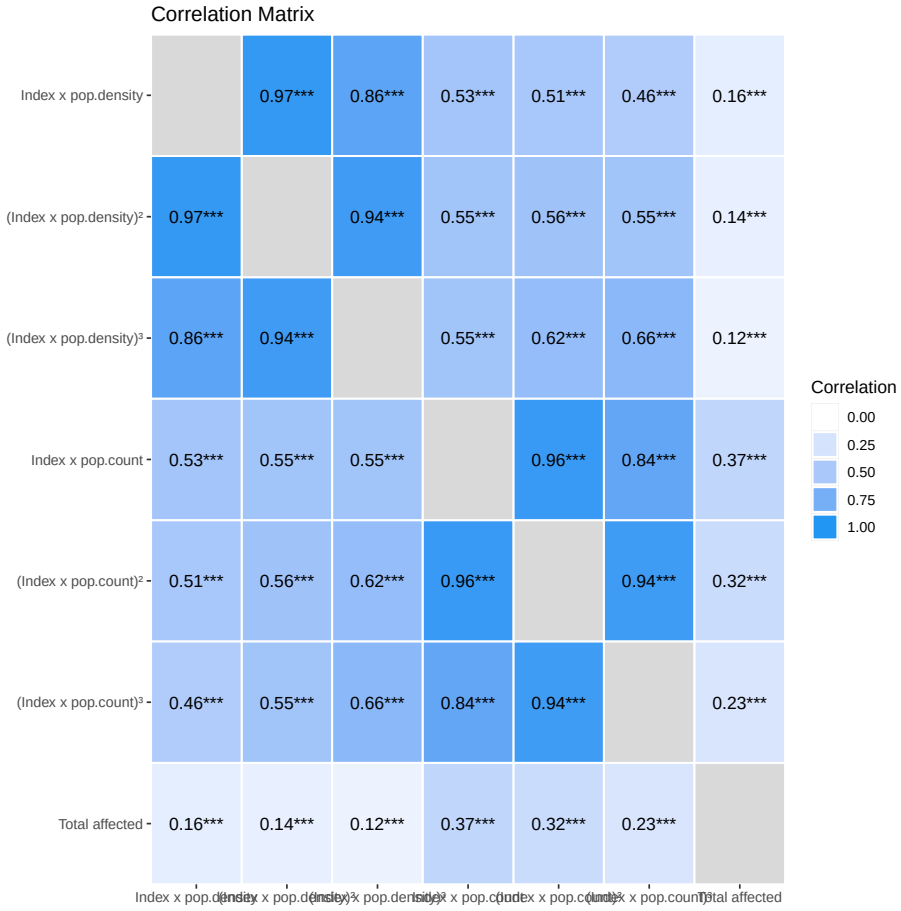


Figure 7: Correlation matrix: Disaster exposure measures

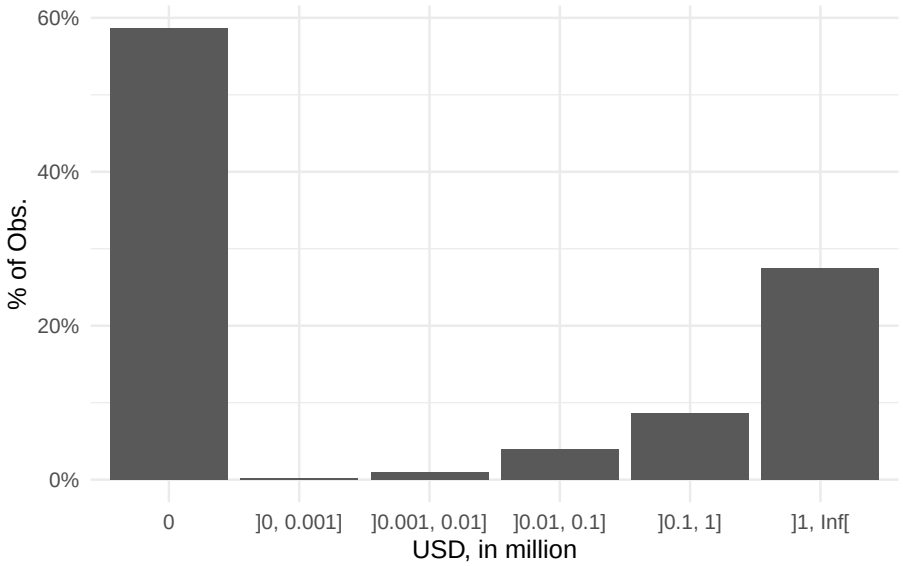


Figure 8: Share of provider-recipient dyads obs. without any commitments

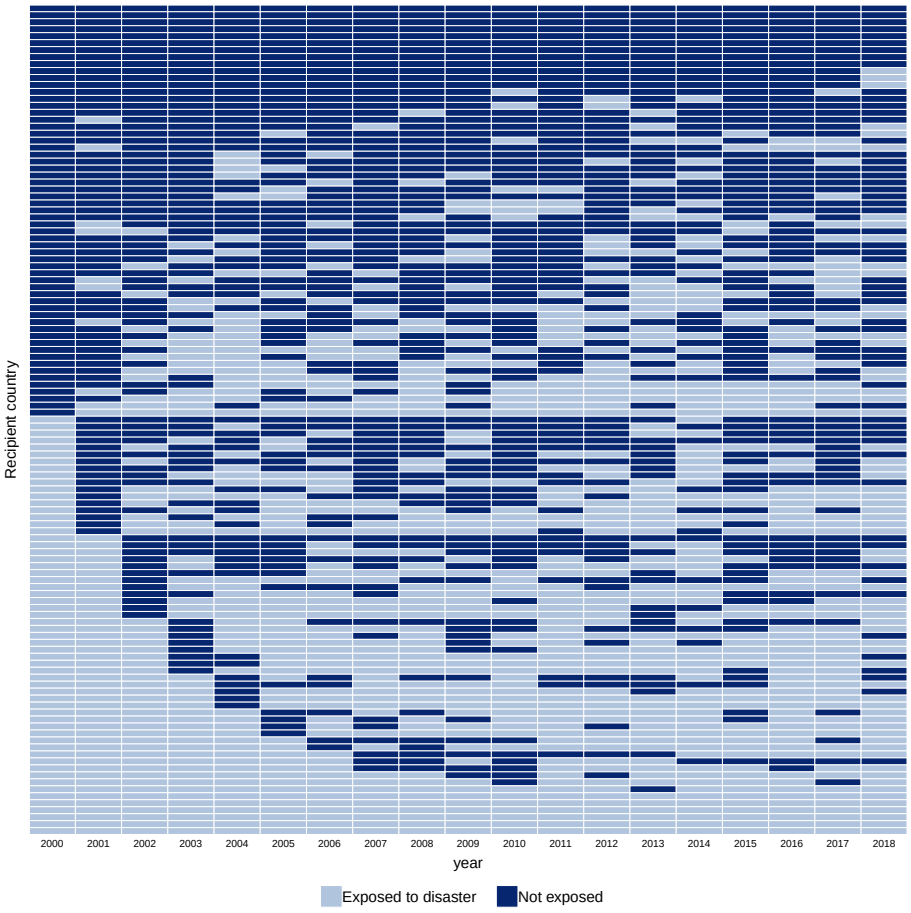


Figure 9: Climate-related disasters occurence in recipient countries, 2005-15

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