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The Speed of Aid: Strategic Urgency in International Emergency Relief

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ABSTRACT

THE SPEED OF AID: STRATEGIC URGENCY IN INTERNATIONAL EMERGENCY RELIEF

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Timely assistance is a precondition for effective emergency relief in the aftermath of natural disasters. This paper shows that donor countries take faster aid decisions if they have stronger strategic interests at stake. We analyze a trilateral panel (donor, donor, recipient) of daily humanitarian aid decisions of 43 donor countries following 516 fast-onset natural disasters between 2000 and 2022. Identification relies on daily variation in donor responses and a series of multidimensional fixed effects. Our analysis reveals a bandwagon effect as donors follow their peers' commitments. This is largely explained by trade competition: the more donors compete over export and import markets, the faster they react to each other. The results are driven by government-to-government aid and underscore the importance of recipient-specific lead donors, who are natural first movers. These findings suggest that commercial competition can distort emergency relief and highlight that strategic interests shape even ostensibly altruistic behavior in international humanitarian aid.

Keywords: humanitarian assistance, disaster relief, aid speed, donor competition, United Nations, emergency appeals, trade competition

JEL classification: F35, F42, F53, H12, H84, O19, Q54

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1 Introduction

More than 7,300 natural and man-made disaster events occurred around the globe since 2000. They caused 1.23 million casualties, affected the livelihoods of more than 4 billion people, and accumulated economic costs of almost USD 3 trillion (CRED & UNDRR, 2020). To cope with these catastrophes, countries often require international humanitarian assistance. Importantly, when earthquakes strike or volcanoes erupt, a difference of a couple of days—if not hours—in the decision to provide aid can save lives and significantly reduce welfare losses (e.g., Clarke and Dercon, 2016; Pople et al., 2021). Accordingly, the international community recognizes speed as an essential element in ensuring the effectiveness of emergency relief. This is formalized in the Principles of Good Humanitarian Donorship (GHD), which emphasize rapid assistance, aiming for "flexible and timely funding" (Principle 5) and "readiness to offer support to the implementation of humanitarian action" (Principle 17).[1]

Individual donors also consistently highlight a rapid response as a top priority. The United States Agency for International Development (USAID), for example, has declared that "[a]ll efforts must be made to ensure that timely and appropriate assistance is efficiently delivered to the neediest victims" (USAID, 2020, p. 4). USAID's Office of US Foreign Disaster Assistance (OFDA) has claimed to be able to send a response team "within hours of an emergency."[2] To provide another example, Ireland's Department of Foreign Affairs emphasizes its goal to "respond effectively, efficiently and in a timely manner to the humanitarian needs of crisis affected peoples" (Irish Aid, 2009, p. 13). Therefore, given the importance of a fast response to disasters, it is crucial to evaluate humanitarian aid activities not only based on their financial volume and distribution (Eisensee and Strömberg, 2007; Strömberg, 2007; Raschky and Schwindt, 2012; Eichenauer et al., 2020; Pathak and Schündeln, 2022), but also on the response's timeliness.

Despite donors' penchant for portraying humanitarian aid as strictly need-based, strategic (especially commercial and geopolitical) donor interests play a considerable role in allocation decisions, both across and within countries (Drury et al., 2005; Fink and Redaelli, 2011; Annen and Strickland, 2017; Bommer et al., 2022). Therefore, also the speed with which donors react to emergencies may be driven not solely

[1]The list of the 24 Principles and Good Practice of Humanitarian Donorship is available at `https://www.ghdinitiative.org/ghd/gns/principles-good-practice-of-ghd/principles-good-practice-ghd.html` (accessed October 2024). Most of the 43 donors that endorse this initiative are included in our empirical analysis.

[2]See the OFDA's fact sheet, available at `https://web.archive.org/web/20250201154931/https://www.usaid.gov/sites/default/files/2022-05/OFDA_Fact_Sheet.pdf` (accessed October 2024). The document was removed following the near-total freeze on foreign aid under the 2^{nd} Trump administration.

by disaster impact and humanitarian concerns. In fact, taking into consideration previous work on donor coordination—or lack thereof (Aldasoro et al., 2010; Fuchs et al., 2015; Davies and Klasen, 2019; Asmus-Bluhm et al., 2025)—, we expect commercial and geopolitical competition between donors to be a particularly important threat to a timely, and thus effective, aid provision. This aligns with Clarke and Dercon (2016, p. 4), who criticize that the global humanitarian system, with its current emphasis on post-disaster management, favors a process of decision-making that may have become "far too politicized, leading to delays, poor decisions, and bad coordination."

Considering how little we know about the speed of aid, we first analyze, descriptively, whether (donor and recipient) political and commercial interests are associated with the speed with which countries decide to provide relief. If aid speed follows the same logic as its allocation, close trade partners and geopolitically relevant countries should receive a more favorable treatment—i.e., faster assistance. Hence, we capture the number of days elapsed from the onset of an emergency until a donor's *first* commitment to provide relief. To do so, we link daily data on humanitarian aid flows from the United Nations (UN) Office for the Coordination of Humanitarian Affairs (OCHA, 2024) to disaster start dates provided by EM-DAT (Guha-Sapir, 2024). The focus on commitment—instead of delivery—dates is justified for both theoretical as well as practical reasons. For one, as we argue later on, the date when the aid decision is taken is the more relevant variable if the goal is to assess donors' strategic considerations (Drury et al., 2005). Second, delivery dates are only available for a small fraction of observations.

Our sample consists of 516 emergencies following fast-onset natural disasters that took place in 128 (recipient) countries between 2000 and 2022, leading to more than 3,500 aid ties with 43 different donor countries.[3] In line with our expectations, we find that donors react faster to natural disasters that occur in countries that are more important trade partners. Geopolitics, however, plays an ambiguous role. While donors appear to pamper close allies with speedy assistance, they also seem to accelerate aid to geopolitical "foes," which aligns with the argument that humanitarian aid serves as a cheap, low-commitment instrument of foreign policy in cases where general development assistance is not politically palatable (Fink and Redaelli, 2011).

To more rigorously investigate whether donor countries' strategic interests—and commercial competition between donors in particular—distort the speed of donors'

[3]Our donor sample includes, in addition to all G20 members, any country that has provided emergency aid at least once a year, on average, in the period between 2000 and 2022. Note that we remove Monaco, as it is a microstate.

aid commitments in the aftermath of natural disasters, we take full advantage of the fine-grained nature of our data by constructing a trilateral panel data set (i.e., donor, donor, recipient) of humanitarian aid commitments at daily frequency. The resulting dataset, with more than 3 million observations, enables us to observe how donor countries move after each other, such that we can investigate whether their (strategic) interactions have consequences for the timing of their aid decisions. Contrary to the existing literature that typically studies the final allocation outcome, we track the whole decision-making process as it unfolds, day after day.

We first hypothesize that how long a donor takes to decide to provide emergency relief is influenced by bandwagon (or herding) effects, such as peer pressure, which we measure by computing the total number of (other) donors that have committed aid during the previous days. As Fink and Redaelli (2011, p. 752) put it, donors "may be exposed to international 'peer pressure' or may want to profit from economies of scale in the provision of aid."[4] Importantly, we expect these forces, which have been shown to influence the final aid allocation (Round and Odedokun, 2004; Fink and Redaelli, 2011; Frot and Santiso, 2011), to matter also for the speed of donor decision-making in the course of emergency events. In fact, we argue that our setting offers an excellent opportunity to identify the ways in which donors influence each other.

In addition, given the widespread evidence of competition between donors (Mascarenhas and Sandler, 2006; Djankov et al., 2009; Davies and Klasen, 2019), we expect that a potential crowding-in effect should vary with the salience of donors' strategic interests—and in particular with the degree of commercial competition between them, which we measure based on the similarity in either export or import structure between a given pair of donors in the disaster-affected recipient country (Finger and Kreinin, 1979). Thus, our second hypothesis is that, when donors observe their competitors providing assistance, they respond quicker in order to secure their interests in the recipient country—be it in terms of protecting their export markets or securing the provision of import goods. Geopolitical antagonism, on the other hand, has less straightforward implications. As already suggested previously, donors may have sensible reasons to favor both "allies" as well as "foes." We take this dimension into account by constructing a measure of geopolitical alignment, which is based on countries' voting pattern at the United Nations General Assembly.

Identification relies on a series of multidimensional fixed effects. Importantly,

[4] It is also possible that countries could instead free ride on the aid donations of other countries, which would imply a crowding-out effect (Davies and Klasen, 2019). This is more likely to be the case when aid has a dominant public-good component.

emergency-day fixed effects for a period of 180 days after each disaster onset absorb all emergency-specific daily variation that is common to all donors on a given day.[5] Thus, we make sure that confounders, such as (common) information flows and media pressure, do not bias the parameters of interest. Identification therefore stems from *within-day variation* in donors' aid decisions for each disaster event. Furthermore, in our strictest specification, we also include donor-specific fixed effects for each emergency. These fixed effects account for unobserved heterogeneity in a donor's response to a specific catastrophe, including the decision itself of whether to provide aid, thus getting rid of a potential selection issue. They also account for each donor's links to a particular recipient country, which include historical, cultural, commercial, and geopolitical ties, and address the fact that donors' expertise may differ according to the type of disaster. In this case, as the aid decision itself is accounted for, we focus solely on the timing of the aid decision, such that we are able isolate the dynamics that accelerate or delay donor response. As we argue in more detail below, the inclusion of these multidimensional fixed effects yields causally-credible estimates of the bandwagon and strategic competition effects.

Our results show, first, that the number of donors that donated during the previous days indeed exerts considerable influence over other donors' speed of reaction. Every additional (first) aid commitment within the previous three days increases the likelihood that another donor decides to provide assistance on a given day by approximately 0.3 percentage points, which is sizable given that the daily average probability to start aiding is below 1%. Second, we find that the extent to which donors follow each other increases with their degree of commercial competition in a given recipient country. Although a competition effect over import markets also exists, donors seem to be particularly sensitive to threats to their export interests: the recent (first) commitment of a donor with the same export structure in the affected country increases the daily aid probability by up to 1.2 percentage points. Possibly due to the reasons discussed above, we do not come to similar conclusions with regard to geopolitical competition between donors.

These findings are robust to a series of tests. Importantly, controlling for potentially confounding factors, such as informational similarity between donors, does not alter any conclusions. Our results are also robust to the use of time windows of different length and accounting for bilateral trade volumes in our competition measures. Reassuringly, we show evidence that donor decisions themselves—and not spurious correlation—trigger the response of other donors, as we do not see significant effects in a placebo test in which we anticipate peer commitments by up to

[5]The 180-day cut-off stems from the UN's definition of a flash appeal.

five days.

To shed more light on the crowding-in effect and more clearly identify the direction of influence between a pair of donors, we leverage the presence of so-called lead donors (Steinwand, 2015), who are arguably the natural first movers during humanitarian crises and are therefore well-positioned to steer the aid behavior of other countries. We find that these (recipient-year-specific) lead donors exert a considerable influence on other donors, serving as an important driver of the crowding-in effect. Notably, their influence is significantly larger than that of ordinary donors, underscoring their potential to accelerate the international aid community's response during humanitarian crises. Once again, export interests play a dominant role. A donor with an export structure similar to the lead donor's in the affected country is up to 2.8 percentage points more likely to commit aid within three days of the lead donor's aid decision. We come to similar conclusions when we analyze the response to donor countries in the G7. Importantly, however, we show that not all donors seem to use emergency relief to engage in disputes over these strategic interests. For a set of "good" donors, who predominantly rely on humanitarian motives to guide their provision of aid (Dreher and Fuchs, 2015), there is, as expected, hardly any evidence of competition.

Moreover, we examine important mechanisms underlying our main findings. We find that both the bandwagon as well as the strategic competition effects are driven by government-to-government aid, rather than aid provided through international and non-governmental organizations. In line with our argument, this type of aid provides the recipient government with more autonomy in deciding how to use the funds, making it more effective for donors seeking to curry favor with recipient countries (Raschky and Schwindt, 2012). This finding further highlights the role of strategic considerations in the speed of emergency aid. Our results show, in addition, that commercial competition between donors is mostly limited to medium-severity disasters. This is consistent with the idea that very severe disasters restrict donors' ability to pursue strategic agendas (e.g., due to public scrutiny), while minor disasters may not attract sufficient attention to warrant efforts to obtain favors from the recipient government.

Taken together, our results show that donor countries react with more urgency in situations where they have stronger commercial interests at stake. Decisions to assist are also affected by the geopolitical relationship between donor and recipient (although not between donors). These findings stand in sharp contrast to the UN Resolution 46/182 (OP2), which states that "humanitarian assistance must be provided in accordance with the principles of humanity, neutrality and impartiality"

(OCHA, 2009) and thus raise important questions about the effectiveness of bilateral humanitarian aid in general. These concerns underscore the necessity to promote mechanisms that foster cooperation and coordination among donors of humanitarian assistance in international fora. As climate change continues to increase the frequency and the intensity of extreme weather events, the urgency and relevance of timely emergency aid after natural disasters are likely to become even more salient in the future (IPCC, 2023).

The attention policymakers and aid practitioners devote to timely relief notwithstanding, this issue has not yet received significant scholarly consideration. To the best of our knowledge, our work is the first to empirically analyze daily foreign aid decisions. Previous research has investigated the speed of aid *disbursements after* the initial aid decision was made (Kilby, 2011; Kersting and Kilby, 2016). Our study is also related to McDowell (2017), who analyzes the speed of loan approval after countries have submitted a letter of intent to the International Monetary Fund.

Our study sets itself apart from previous work in three key ways: (i) we focus on emergency aid, where response times are measured in days rather than months, making speed an even more decisive factor for effectiveness; (ii) we leverage fine-grained daily data that allows for a more precise analysis of decision-making dynamics and interactions between donors—importantly, we observe donor decisions as emergency events unfold, and not only the final aid allocation; and (iii) we explore the influence of strategic donor competition on response times in the context of humanitarian aid—an area often presumed to be less politicized.

More broadly, we contribute to the economics literature on international humanitarian assistance (Strömberg, 2007; Raschky and Schwindt, 2012; Becerra et al., 2014; Nunn and Qian, 2014; Becerra et al., 2015; Raschky and Schwindt, 2016) and, in particular, to the strand that is concerned with the determinants of its allocation decisions (Eisensee and Strömberg, 2007; Annen and Strickland, 2017; Fuchs and Öhler, 2021; Mogge et al., 2023). Our work extends this literature by shifting the focus from the traditional questions of "to whom?" and "how much aid?" to the crucial question of "how fast?," demonstrating that strategic donor interests not only influence aid volumes but also response times.

Our analysis also contributes to a rich strand of research on aid donor interactions, which includes studies of both coordination (Djankov et al., 2009; Aldasoro et al., 2010; Bourguignon and Platteau, 2015) and competition (Fuchs et al., 2015; Steinwand, 2015; Davies and Klasen, 2019) between donors. Despite broad acknowledgment of a widespread lack of coordination and frequent speculation about the harm it creates, the current empirical and theoretical understanding of the underlying causes of donor fragmentation is still rudimentary at best (Steinwand, 2015). We contribute to this debate by analyzing on-going aid decisions after a clearly identified event. By, roughly speaking, watching the response to disaster emergencies as it unfolds, day after day, we are able to identify new patterns of interaction and competition among donors as well as important features of the political economy of aid that have been neglected so far. Because we are not limited to examining only the final picture, as most of the previous literature is, our vantage point lets us track the implications that the decision of one donor has for other aid providers "on the go." Thus, in addition to observing who is moving after whom, we can single out strategic drivers of daily aid decisions.

Finally, we contribute to the literature on the economics of natural disasters (e.g., Kahn, 2005; Noy, 2009; Strobl, 2011; Strobl, 2012; Cavallo et al., 2013; Felbermayr and Gröschl, 2013; Felbermayr and Gröschl, 2014; Kunze, 2021). Previous work has explored the (mostly adverse) economic and political effects of natural disasters around the globe, including declines in life satisfaction, reduced life expectancy, increased migration, and heightened conflict risk (Neumayer and Plümper, 2007; Nel and Righarts, 2008; Luechinger and Raschky, 2009; Boustan et al., 2012; Berlemann, 2016). Our analysis of aid response times adds a crucial dimension to understanding how the international community reacts to these adverse effects with humanitarian assistance, highlighting how strategic interests may compromise the speed and thus arguably the effectiveness of such efforts.

While our study examines the international political economy across a comprehensive set of global disaster events, our findings parallel an important strand of literature that analyzes domestic political economy in the context of specific disasters. Most relevant to our study, there is evidence that domestic aid allocation decisions are shaped by political considerations, including co-partisanship between local and national leaders, ethnic favoritism, voter behavior, and electoral cycles (Cole et al., 2012; Pathak and Schündeln, 2022; Schneider and Kunze, 2023; Berlemann et al., 2024). By analyzing the speed of emergency aid decisions through the lens of international donor competition, our study reveals a crucial but previously unexplored mechanism through which political economy considerations shape the effectiveness of disaster relief efforts in addition to those studied at the domestic level.

We proceed as follows: Section 2 describes how we measure the speed of aid decisions after fast-onset natural disasters and provides several stylized facts, highlighting how response speed relates to commercial competition and geopolitical ties. In Section 3, based on daily (i.e., emergency-day) aid decisions, we present our main analysis, testing the bandwagon and strategic competition hypotheses. Robustness tests are discussed in Section 4. In Section 5, we investigate potential mechanisms. Finally, Section 6 offers concluding remarks.

2 Measuring the Speed of Aid

2.1 Humanitarian Aid and Natural Disasters

Humanitarian aid consists of "intervention[s] to help people affected by natural disasters and conflict to meet their basic needs and rights" (OCHA, 2024). Throughout our study, we rely on data on humanitarian aid flows provided by the Financial Tracking System (FTS) of the UN Office for the Coordination of Humanitarian Affairs (OCHA, 2024) and restrict our analysis to flows that have been linked to a particular natural disaster in FTS, which are events that typically lead to a UN emergency appeal. Particularly in these cases, a fast provision of aid is key to its success (Clarke and Dercon, 2016).

The FTS tracks flows worldwide and is based on self-reported information, which is provided by donor governments and/or recipient agencies, collected from donor websites, or quoted in pledging conferences.[6] The FTS is widely used in policy analysis and academic research (e.g., Fink and Redaelli, 2011; Raschky and Schwindt, 2012; Eichenauer et al., 2020) and is arguably the best database available for analyses of humanitarian aid that, like ours, are not restricted to OECD donors, but rather encompass a wide range of donor countries.[7]

While the database covers information on aid flows provided by more than 160 bilateral donors, including infrequent donor countries such as the Democratic Republic of Congo and North Korea, we focus on donor countries with significant aid activities. As such, we limit our analysis to G20 members and all other countries that have provided emergency aid after at least one fast-onset natural disaster event per year, on average. In other words, we remove donor countries that do not satisfy the threshold of 23 records of emergency aid provision in the sample period (2000–

[6]In cases where donation data stem from various sources, FTS invests significant efforts into cross-validation and reconciliation. For a more detailed description of the data collection and subsequent cross-checking process, see OCHA (2004). By comparing FTS records with data of the OECD's Development Assistance Committee, Fink and Redaelli (2011) find only minor differences between both databases, which shows that FTS has relatively good data coverage. See Harmer and Cotterrell (2005) for a discussion of strengths and weaknesses of FTS data.

[7]In contrast to the commonly used OECD Creditor Reporting System and the project-level database AidData (Tierney et al., 2011), FTS has the advantage that the it covers virtually every country in the world. Even countries with a low aid transparency, like China and Saudi Arabia, are covered by FTS.

2022). We are left with 43 donor countries with 3,500 emergency aid linkages with 128 recipient countries. While FTS reports humanitarian aid flows contributed, committed, and pledged, we exclude the latter as these represent only a "non-binding announcement of an intended contribution or allocation by the donor" (OCHA, 2024). Appendix Table A1 reports all donor countries in our sample together with the number of (first) aid provisions, amount contributed, and average speed in days.

To be able to compute the speed of aid and establish several stylized facts, it is crucial that the database links humanitarian aid flows directly to specific natural disasters and contains information on aid decision dates. We make use of the *decision date* variable from FTS, which captures the "[d]ate on which a donor is reported to have made a funding commitment."[8] Inspired by Fuchs and Klann (2013), we then measure the speed of country i's aid decision after disaster event k in recipient country r by computing the duration, in days, from disaster onset, $StartDate_{i,k,r,t}$, until the day on which donor i first decided to provide assistance to recipient r to cope with disaster event k, $DecisionDate_{i,k,r,t}$. Formally, we define:

$$Duration_{i,k,r,t} = DecisionDate_{i,k,r,t} - StartDate_{i,k,r,t} + 1 \quad (1)$$

where data on $DecisionDate_{i,k,r,t}$ come from FTS, as explained above, and information on $StartDate_{i,k,r,t}$ is taken from the International Disaster Database (EM-DAT), maintained by the Centre for Research on the Epidemiology of Disasters (Guha-Sapir, 2024).[9] This required going through a careful process of assigning each humanitarian aid flow, from FTS, to the corresponding disaster reported by EM-DAT. This task was performed, independently, by at least two different coders. We then arbitrated in the case of any discrepancies.

If a donor commits to provide aid on the start day of the disaster event, $Duration_{i,k,r,t}$ takes a value of 1. Higher values imply slower aid speed.[10] As already mentioned above, since we study emergency assistance, we only include aid flows with a decision time smaller than or equal to 180 days. Aid delivered with longer delays hardly aims at urgent needs that require speedy assistance, and the selection of 180 days as cut-off level is in line with the UN's definition of a flash appeal, which struc-

[8]See FTS glossary at https://fts.unocha.org/glossary (accessed October 2024).

[9]The database covers information on disaster characteristics, such as the disaster type, magnitude, number of people affected, number of people killed, and—crucial for our purposes—the start and end dates. All disasters included in the data set must meet at least one of the following criteria: (i) 10 or more people have died, (ii) 100 or more people have been affected, (iii) a state of emergency has been declared, or (iv) a call for international assistance has been made in response to the wreck.

[10]In the case of storms, to account for donors' efforts toward disaster preparation, all aid decisions taken in the week before the onset are assumed to have been made on day 1.

tures a coordinated humanitarian response for up to six months after the start of an emergency. Importantly, we focus on decision date—instead of delivery date—because this is arguably the dimension with most room for strategic considerations and therefore the purest measure to assess how donors respond to each other (Drury et al., 2005). Delivery dates, on the other hand, are subject to other contingencies that may obfuscate donors' preferences and priorities. Additionally, data on delivery dates are less precise and only available for 7% of the sample. As the FTS acknowledges in its glossary, "[i]f this [delivery] date is not available, FTS uses the decision date or as last resort, the date the information was reported to FTS."[11]

Moreover, to be able to precisely measure the speed and timing of humanitarian aid, we restrict our analysis throughout the paper to disaster types with a clearly identifiable start date. This means that we, similarly to Fink and Redaelli (2011), limit the sample to fast-onset disasters and thus exclude events such as drought, extreme temperature, and insect infestation. The remaining disaster types include earthquakes, floods, mass movements (or landslides), storms, and volcanic activity. In a second step, we keep only those events for which EM-DAT records a precise start day—i.e., we exclude entries for which only the start month or year is available.[12] This focus on fast-onset disasters comes with the advantage that it mitigates endogeneity concerns, because the exact timing of these disasters is largely unpredictable.[13] Furthermore, the natural catastrophes themselves typically do not last more than a day—in contrast to the humanitarian catastrophe that they trigger, which can last much longer. Hence, differently from slow-onset events, such as cold winters or droughts, there is no reason to believe that the speed of aid may affect the occurrence and timing of a rapid-onset disaster nor whether and when such event is considered to be a humanitarian crisis.

Our final sample consists of 446 fast-onset disasters. Since 29 of these affect more than one country at the same time, we end up with 516 emergencies, which we define as a humanitarian crisis following a disaster event in a specific country.[14] Table 1 reports, by disaster type, information on the frequency and severity of the events in our sample. For each group, it also shows the average number of donor countries that provides assistance as well as the fastest donor to respond (on average). Appendix Table A2 provides descriptive statistics of all variables.

[11]See FTS glossary at https://fts.unocha.org/glossary (accessed October 2024).

[12]The precise start date is missing for 18 disasters (or about 4% of all disaster in the sample).

[13]While earthquakes cannot be reliably predicted, storms are, at best, predictable two weeks in advance (Zhang et al., 2019).

[14]For example, we treat the 2004 Indian Ocean tsunami as nine emergencies as it affected nine countries in our sample: India, Indonesia, Malaysia, Maldives, Myanmar, Seychelles, Somalia, Sri Lanka, and Thailand.

Table 1 – Fast-onset Natural Disasters (2000–2022)

Disaster type	No. of events	Avg. no. people killed	Avg. no. people affected	Avg. no. donors	Fastest donor (Avg. days)
Earthquake	81	28,491	2,958,217	23	Indonesia (4.5)
Flood	255	227	3,336,679	12	India (14.5)
Mass movement (wet)	19	331	62,087	11	Italy, Singapore (4)
Storm	143	7,092	1,910,771	15	Israel (7)
Volcanic activity	18	135	75,397	12	Belgium, Finland, Turkey (5)
All	516	9,871	2,711,719	16	Indonesia (10.1)

Notes: The table shows, for each type of fast-onset disaster, the number of events, the average number of people killed and affected, the average number of donors that responded, and the fastest donor. The fastest donor is selected based on the lowest average duration, in days (shown in parentheses), between disaster start and first aid commitment. Data from EM-DAT (Guha-Sapir, 2024) and FTS (OCHA, 2024) for the period between 2000 and 2022.

2.2 Stylized Facts

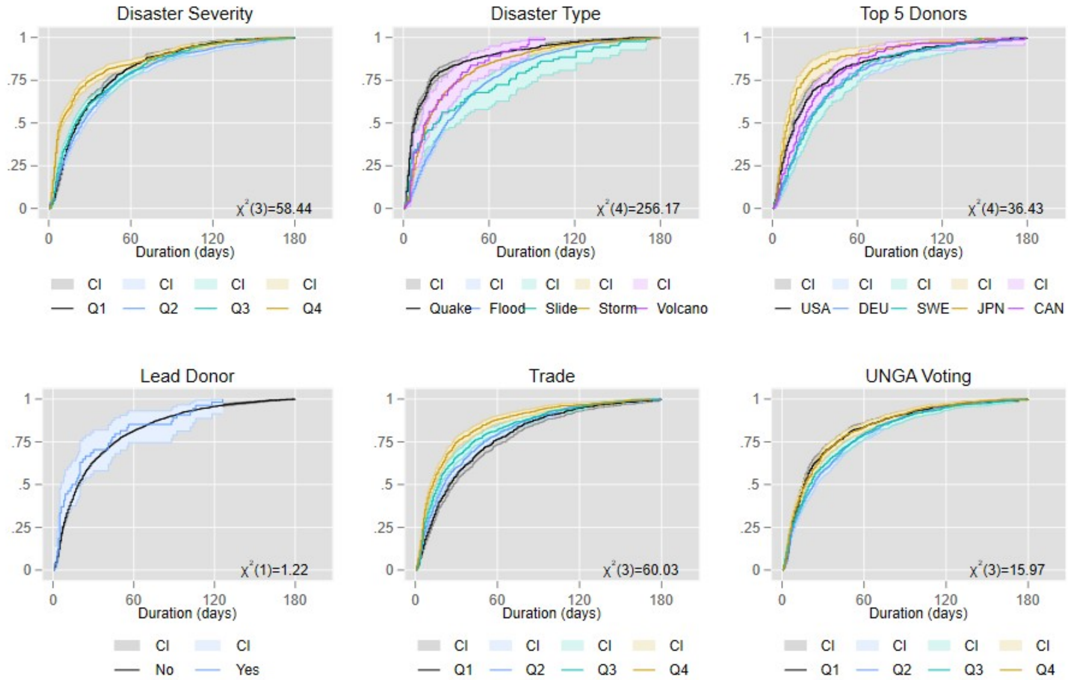
We start with a descriptive (survival) analysis of our data at the emergency level, which produces several stylized facts.[15] For donor countries that eventually provide emergency relief in response to a fast-onset natural disaster, we analyze the timing of their first aid decisions. Specifically, we calculate their failure functions, which represent the probability that a country will make an aid decision ("fail") at a given time point, conditional on not having donated up to that point. We observe that these functions differ significantly according to some disaster characteristics and donors' strategic interests.

Stylized Fact 1: Donor countries respond faster to the most severe disasters. The top-left panel of Figure 1 displays the failure functions for each quartile of disaster severity. We measure disaster severity with the number of people killed, which is provided by EM-DAT (Guha-Sapir, 2024). We find that donors react particularly fast to emergencies in the top quartile of the fatality distribution, whereas the differences between the other three quartiles are much less pronounced. In our sample, of all the 729 aid decisions involving disasters in the top severity quartile, only around 5% (39) had not yet been made by the 50th day after the onset. For each of the other quartiles, the share of yet-to-be-decided commitments by the 50th day is 19% or higher. This suggests that aid speed is, at least to some extent, responsive to humanitarian needs.

Stylized Fact 2: Donor countries respond faster to earthquakes than to other disaster types. It is conceivable that different types of disasters trigger different responses from the aid community, thus potentially also affecting the speed of aid. For example, Eisensee and Strömberg (2007) report that the newsworthiness of emergencies depends on disaster type. The top-middle panel of Figure 1 displays

[15]We use duration models to allow for the probability of deciding to provide aid to depend on the time elapsed since the disaster onset.

Figure 1 – Stylized Facts: Failure Functions



Notes: The figure shows Kaplan-Meier failure functions according to the following characteristics: (i) quartiles according to disaster severity, based on the number of people killed by each disaster (top-left); (ii) disaster type, i.e., earthquakes, floods, landslides, storms, and volcanic activity (top-middle); (iii) for each of the top five donor countries in the sample in terms of the number of aid provisions, the United States (USA), Germany (DEU), Sweden (SWE), Japan (JPN), and Canada (CAN) (top-right); (iv) whether the donor is a considered to be a lead donor as defined in Section 3 (bottom-left); (v) quartiles according to the bilateral trade volume (exports and imports) between donor and recipient (bottom-middle); and (vi) quartiles according voting alignment between donor and recipient at the UNGA (i.e., $\Delta UNGA$). The figure shows 95% confidence intervals.

the failure functions for each disaster type. We observe significant differences in the speed of aid. Donor countries' response time is the shortest after earthquakes. This finding does not seem to be driven by different disaster types being intrinsically more or less catastrophic, as we come to the same conclusion in a regression setup that accounts for disaster severity and recipient need (Appendix Figure A1). Specifically, we control for the logged number of people killed and people affected (both from EM-DAT), the logged and lagged recipient GDP per capita and population size (both from World Bank, 2024), and donor-recipient and year fixed effects. Notably, donors are on average almost 12 days faster to respond to earthquakes than to floods. Among other things, this is consistent with the evidence that media coverage—which varies across disaster types and devotes particular attention to earthquakes—influences donor behavior (Eisensee and Strömberg, 2007).

Stylized Fact 3: There is significant variation in response time across donor countries. Among the top 20 donor countries in terms of the number of aid provisions in the sample, Japan is, on average, the fastest to decide to provide assistance. This is illustrated by the top-right panel in Figure 1, which shows the failure functions of the top five donors: the United States, Germany, Sweden, Japan, and Canada. On average, while Japan takes 15 days to make its first aid commitment, the United States—the most active donor in our sample—needs significantly longer, 21 days ($p = 0.016$). This finding is corroborated by a regression analysis that includes the top five donor countries in the sample and controls for the logged number of people killed and people affected, logged and lagged recipient GDP per capita and population size, as well as disaster-type, recipient, and year fixed effects (Appendix Figure A1). Relative to the average donor country in the sample, Canada, Japan, and the United States are significantly faster to commit assistance, while Germany is significantly slower.

Moreover, the bottom-left panel in Figure 1 shows that lead donors are faster than their peers. A lead donor is a country that not only is the most important aid provider for a given recipient country, but also maintains long-term (often historical) ties with it. We will further develop—and properly define—this concept in Section 3. For now, it suffices to say that there seems to be a certain set of (recipient-specific) prominent donors that are not only faster, but may also be particularly influential in their spheres of influence.

Stylized Fact 4: Donors respond faster to emergencies that take place in countries that are more important trade partners. Considering the widespread evidence that the cross-country allocation of humanitarian aid is influenced by commercial interests (Fink and Redaelli, 2011), we investigate whether close trade partners receive speedier assistance. Such a preferential treatment may help, for instance, mitigate the damage to commercial ties caused by catastrophes (Gassebner et al., 2010). If a donor country exports a substantial part of its production to a country that was hit by a natural disaster, it may be inclined to provide aid faster than usual to make sure that its exports do not lose their market. Likewise, donors that rely on particular countries for crucial imports should react more quickly to avoid having their supply chains disrupted.

In both cases, emergency relief can cushion the impact of the disaster on trade in at least three ways. First, it may directly contribute to repairing crucial trade infrastructure, such as ports and roads. Second, by providing quick assistance, donor countries can help reduce, indirectly, the impact on aggregate economic activity that often follows natural disasters and may in turn affect trade ties. Finally, the faster a donor acts, arguably the more likely its assistance is going to be seen as a gesture of goodwill by the affected country, and thus more likely it is to help preserve (or even boost) existing commercial ties.

We measure the intensity of trade ties with the sum of exports and imports flows (in constant 2010 US dollars) between donor and recipient and then divide the sample in quartiles according to the bilateral trade value (data from IMF, 2024). The survival analysis indicates that donors respond significantly faster to disasters in recipient countries that are more important commercial partners. As we show in the bottom-middle panel of Figure 1, the higher the trade quartile, the faster donors respond on average. Appendix Figure A2 reveals that, in fact, both exports and imports are associated with a faster response. Moreover, we find similar evidence in a regression model that controls for the logged number of people killed and people affected, logged and lagged recipient GDP per capita and population size, and donor, recipient, and year fixed effects. Donors in higher quartiles respond more quickly: compared with the bottom quartile, the time required to commit is on average four, six, and nine days shorter for donor-emergency pairs in the second, third, and fourth quartiles, respectively (Appendix Figure A1).

Stylized Fact 5: Donors provide faster assistance to the most and least geopolitically aligned countries. Geopolitics is another factor that may distort the delivery of humanitarian aid. To assess the role played by political alignment between donor and recipient, we use information on the voting alignment at the UN General Assembly between these countries.[16] More precisely, our indicator of political alignment between donor i and recipient r is the absolute difference of their ideal points, as calculated by Bailey et al. (2017).[17] That is, $\Delta UNGA_{i,r,t} = |idealpoint_{i,t} - idealpoint_{r,t}|$.

However, it is not clear, *a priori*, how political alignment affects the speed of humanitarian assistance. On the one hand, closer political ties could be associated with countries receiving faster aid from their allies as donors may speed up their emergency aid to express their support for befriended countries or to help ensure the survival of politically aligned governments in cases where a severe disaster threatens political stability (Drury and Olson, 1998; Drury et al., 2005). On the other hand, donors may give preferential treatment to persuade adversaries or recipients that are politically distant to make concessions to the donor in the future, given that emer-

[16] Measures of UN voting alignment are widely used in the empirical aid literature (e.g., Thacker, 1999; Kilby, 2009; Kilby, 2011; Faye and Niehaus, 2012; Kersting and Kilby, 2016; Dreher et al., 2021). See Dreher et al. (2024) for a literature review.

[17] For each year, Bailey et al. (2017) estimate a country's ideal point within a one-dimensional preference space. A country's voting behavior (i.e., yes, no, or abstain) in each UNGA vote is modeled as a function of its ideal point. Therefore, the more similar the voting behavior of two countries, the closer their ideal points will be, resulting in a smaller absolute difference between the two.

gency assistance tends to be a more appropriate tool to buy policy concessions from less aligned countries than general development assistance. In contrast to the former, the provision of assistance aimed at long-term economic and structural development requires a fair amount of collaboration between donor and recipient and hence at least some goodwill to facilitate negotiations (Fink and Redaelli, 2011; Annen and Strickland, 2017). Emergency aid, on the other hand, requires hardly any negotiation and considerably less coordination with recipient countries and thus presents donors with the opportunity to engage with recipient countries that are less politically aligned by making use of more flexible and low-commitment arrangements.

The bottom-right panel of Figure 1 indicates that indeed both seem to be true, as donor-recipient pairs at the extremes of the distribution of $\Delta UNGA$ (first and fourth quartile) display shorter response times than observations in quartiles two and three. That is, donors commit aid more quickly if the disaster affects either a closely aligned country (Q1) or a country with a very different geopolitical agenda (Q4). Apparently, donors both reward closely aligned governments *and* try to sway countries that are out of their sphere of influence.[18]

The case of the 2010 Haiti earthquake provides a prime example of these two opposing mechanisms. In the aftermath of the disaster, the Republic of China (Taiwan)—which back then maintained diplomatic relations with only 14 countries, including Haiti—engaged in a large-scale humanitarian mission. Taipei's first rescue team reached Haiti on January 16 and the first medical team arrived five days later. (The People's Republic of) China, which considers Taiwan a renegade province and attempts to isolate the island diplomatically, showed similar generosity towards Haiti, despite refusing diplomatic relations with the government in Port-au-Prince as a consequence of Haiti's diplomatic recognition of Taiwan. Tubilewicz (2012, p. 6) describes these activities of the two Asian donors as "aid competition." Beijing's first rescue team reached Haiti two days *before* the one sent by Haiti's close ally Taiwan. In line with the behavior of China in the case of the Haiti earthquake, Fink and Redaelli (2011) find politically *less* affine countries to be more likely to receive emergency aid from a particular donor.

Summing up, we conclude that the speed of aid shows considerable variation across levels of disaster severity, disaster types, donor countries, and the strength of geopolitical and commercial ties. We focus on the latter and move to a more rigorous empirical setting to analyze strategic competition in the speed of emergency aid.

[18] Appendix Figure A3 presents the same finding in a different manner, as it splits the sample only in two groups based on whether donor-recipient pairs are at the extreme (Q1 and Q4) of the distribution or not (Q2 and Q3). However, these findings are not statistically significant at conventional levels in a related regression model presented in Appendix Figure A1.

3 Daily Analysis

To delve deeper into donor decision-making on the speed of emergency aid, we turn our analysis to the emergency-day level. For each disaster event, we study how donors' daily decisions to provide (or withhold) aid are affected by their peers.[19] Specifically, we analyze how two key factors influence the timing of humanitarian aid commitments: (i) bandwagon effects, measured by the number of donors who have committed assistance to address a particular emergency, and (ii) the extent to which donors compete—particularly due to commercial interests—in the affected country.

Accordingly, we test two hypotheses. First, we posit that recent aid commitments by other donors significantly increase a donor's likelihood of providing assistance (*bandwagon hypothesis*), as donors frequently observe and take cues from their peers—particularly from well-connected countries with on-the-ground expertise—either through informal exchanges or formal discussions in international organizations. We expect these dynamics to influence not only whether donors provide aid, but also *when* they decide to do so.[20] Alternatively, it is possible that a donor's commitment discourages the aid provision of other donors. This may be especially likely in cases in which aid is seen as an international public good (Schweinberger and Lahiri, 2006). Yet, based on the cross-country literature on aid allocation, we expect the positive effects of peer influence to outweigh any crowding-out effects.[21]

Second, we hypothesize that donors' reactions to their peers are mediated by their strategic interests (*competition hypothesis*). Specifically, the more the interests of a particular donor conflict with those from an "active" peer, defined as a donor that has committed aid within the previous three days, the faster we expect the former to react to the decision of the latter. This implies that the influence that donors have on each other varies depending on their degree of competition. That is, on top of a bandwagon effect, we expect commercial competition to amplify responsiveness

[19] Note that this is not a duration analysis as the outcome of interest is a binary variable that captures whether a donor commits aid on a given day. In our regression setup also the explanatory variables vary on a daily basis. Moreover, data censoring is of little concern, as we observe donors' decision-making up to 180 days after disaster onset. If they have not decided to assist until then, but would still do so at some later stage, it would hardly classify as emergency relief anyway.

[20] Our baseline analysis examines the impact of aid commitments made within the last three days as decision-making might be hampered through bureaucratic processes and weekends. This also accounts for differences in time zones. Since this decision is arbitrary to a certain extent, we document the robustness of our results to windows of different lengths in Section 4.

[21] There is considerable evidence suggesting that aid decisions are often influenced by bandwagon effects from other donors (e.g., Round and Odedokun, 2004; Fink and Redaelli, 2011). So far, however, this herding behavior has only been observed in the final allocation, which makes it difficult to assess whether donors happen to make, autonomously, similar decisions or rather respond to one another.

when rival donors vie for the goodwill of and influence in the recipient country. A donor is arguably more likely to engage to secure its interests if its rival has recently done so, such that the net effect that donors have on each other should vary according to their degree of competition. We focus on two particular sources of commercial competition between donors: exports and imports interests. Later, we take also geopolitical interests into consideration.

3.1 Empirical Strategy

To test our hypotheses, we take full advantage of the daily nature of our data. We construct a panel data set in which the unit of analysis is donor-emergency by day. That is, for every disaster event, we observe each of our 43 donor countries for a maximum of 180 days from disaster start or until the day in which the donor (first) decides to provide aid.[22] We thus analyze whether and how, during a specific emergency, the decision to provide aid on a given day is influenced by the behavior of other donors that committed to assist within the last three days. According to the bandwagon hypothesis, these previous commitments should encourage other donor countries, which have not yet committed to assist, to accelerate their aid decision.

To investigate the role of commercial interests in donors' response to their peers, we examine the (sectoral) trade overlap between a pair of donors in a given aid recipient country. Arguably, the higher the (lagged) overlap, the more likely it is that donors compete on that given market. We thus follow Finger and Kreinin (1979) and calculate both export and import similarity indices for each donor pair in a particular recipient country.[23] More precisely, the Export Similarity Index, ESI, of donor countries i and j in recipient country r and year t is given by:

$$ESI_{i,j,r,k,t} = \sum_{s} Min(X_s^{i,r,k,t}; X_s^{j,r,k,t}) \in [0,1] \qquad (2)$$

where $X_s^{i,r,k,t}$ represents donor i's exports in sector s to recipient r in year t as a share of i's total exports to r in t. Sectoral international trade data (SITC, Rev. 2) come from Growth Lab (2024). Analogously, we use the sectoral import data to calculate the Import Similarity Index (ISI). Both ESI and ISI take values between zero and one, with one indicating perfect similarity. The more similar the export or import structure of a pair of donors in a given recipient country, the more we expect them to compete with each other. To make sure that the similarity is not affected by the

[22] As already mentioned above, the selection of 180 days as cut-off level is in line with the UN's definition of a flash appeal.

[23] See Fuchs et al. (2015) and Asmus-Bluhm et al. (2025) for applications of the export and import similarity indices in the empirical aid literature.

emergency, we take the value from the year before the disaster. Appendix Figure A4 illustrates these measures by displaying the average ESI and ISI between two major donors in our sample, the United States and Japan, in each recipient country.

Our goal is to analyze how donors respond to the collective pressure of recent aid commitments, rather than to individual donor countries. Therefore, we extend these measures and construct weighted sums of ESI and ISI to take the daily collective competitive pressure into account. Specifically, we sum all donors who declared their first aid commitment within the previous three days, weighting each by either their export or import similarity index (in the previous year, $t-1$). These aggregate measures of export and import competition (*ExpComp* and *ImpComp*, respectively) are calculated as follows:

$$ExpComp_{i,j,r,k,[d-3,d-1]} = \sum_{j} Aid_{j,k,r,[d-3,d-1]} \times ESI_{i,j,r,k,t-1} \tag{3}$$

$$ImpComp_{i,j,r,k,[d-3,d-1]} = \sum_{j} Aid_{j,k,r,[d-3,d-1]} \times ISI_{i,j,r,k,t-1} \tag{4}$$

Therefore, $ExpComp_{i,j,r,k,[d-3,d-1]}$ and $ImpComp_{i,j,r,k,[d-3,d-1]}$ capture the aggregate daily competitive pressure faced by donor i by weighting all donors ($j \in J$) that decided to provide assistance in the previous three days by their trade similarity with donor i in recipient country r. To illustrate how the aggregation works, consider the 7.2-magnitude earthquake that hit eastern Türkiye on October 23, 2011. On the next day, France and Russia were the first donors to commit assistance. One day later (October 25), Japan decided to provide aid, followed by Austria on October 26. As an example, the *ExpComp* assigned to Spain on October 27, when the country committed to assist, is 2.002, which is the sum of Spain's lagged (i.e., 2010) export similarity index (relative to Türkiye) with France (0.696), Russia (0.199), Japan (0.591), and Austria (0.516) combined, which are the donors that made their aid decision in the three days before Spain's.

With this in mind, we proceed to estimate the following linear probability model using ordinary least squares:

$$\begin{aligned} Aid_{i,k,r,d} = {} & \gamma_1 NDonors_{j,k,r,[d-3,d-1]} + \gamma_2 ExpComp_{i,j,k,r,[d-3,d-1]} + \\ & \gamma_3 ImpComp_{i,j,k,r,[d-3,d-1]} + H(Days_{i,k,r,d}) + \\ & \eta_d + \theta_d + \kappa_d + \lambda_i + \pi_{k,r} + \upsilon_{i,k,r,d} \end{aligned} \tag{5}$$

where the dependent variable, $Aid_{i,k,r,d}$, is binary and indicates whether donor country i, on day d, decides to provide humanitarian assistance (for the first time) to recipient country r in response to emergency k. On the right-hand side of the equation, we include the number of donors that decided to start providing assistance to disaster k in recipient country r within the last three days, $NDonors_{k,r,[d-3,d-1]}$, and the two measures of aggregate daily competitive pressure introduced above, $ExpComp_{i,j,k,r,[d-3,d-1]}$ for exports and $ImpComp_{i,j,k,r,[d-3,d-1]}$ for imports. In terms of the discussion above, the bandwagon hypothesis implies a positive γ_1 and the competition hypothesis requires positive γ_2 and/or γ_3.

Moreover, in equation 5, we add a polynomial function, $H(.)$, of the number of days passed between disaster start and the decision date of donor i to provide its first assistance to take into consideration a potential (non-linear) influence of the total time passed since the disaster onset.[24] To account for unobserved characteristics that may influence the timing of aid provision, we include in all specifications weekday (η_d), day-of-the-month (θ_d), month (κ_d), donor (λ_i), and emergency-recipient fixed effects ($\pi_{k,r}$). We are thus able to remove, for instance, all the time-invariant (during a particular emergency) donor and recipient characteristics that affect decision-making—such as donor aid infrastructure and particularities of each type of disaster—but are unrelated to the influence of other donors.

In our preferred specifications, we also include emergency-day and emergency-donor fixed effects. The former absorb all emergency-day-specific variation that is common to all donors on a given day. This rules out that our results are driven by confounding factors, such as disaster repercussions (like aftershocks) or new information about the severity of emergencies becoming available to the international community. Identification in this setting therefore stems from *within-day variation* in donors' aid decisions relative to a particular emergency. As such, we are able to pin down in which ways a donor's decision (not) to follow the decision of other donors depends on its strategic interests. Although this comes with the disadvantage of no longer being able to estimate γ_1 (and thus test the bandwagon hypothesis), it significantly improves the identification of γ_2 and γ_3 and hence our ability to test the competition hypothesis.

In turn, emergency-donor fixed effects—22,187 binary variables for each donor-emergency pair—account for all time-invariant (during the 180-day emergency period) and disaster-specific donor characteristics. This includes the decision of whether to provide aid at all, therefore taking care of any potential selection issue. Moreover, this approach also captures donors' different levels of expertise with specific disas-

[24] In our baseline specification, we control for a polynomial function of degree 3. Note that this polynomial becomes redundant in specifications with emergency-day fixed effects.

ter types, historical or geopolitical ties with disaster-affected countries, as well as domestic pressures, influenced for instance by media coverage or diaspora networks. Consequently, in this case our analysis focuses solely on the timing of donors' first commitments, which enables us to isolate the dynamics that accelerate or delay their response.

3.2 Main Results

Table 2 presents the main results. We examine whether donors react to the aid decision of other donors and whether this reaction is a function of export and import competition. We find that aid patterns are contagious: each new donor in the past three days measurably increases the probability of new donors today, lending support to the bandwagon hypothesis. All else being equal, the likelihood that a donor commits to aid increases by 0.3 percentage points (column 1) for every additional commitment. This effect is sizable in light of the average daily probability to aid (0.1%) after a given fast-onset disaster.

Table 2 – Bandwagon and Competition: Main Results

	Dependent Variable: *Aid*					
	(1)	(2)	(3)	(4)	(5)	(6)
No. of donors	0.003***	-0.000		0.002***	0.000	
	(0.000)	(0.000)		(0.000)	(0.000)	
Export Competition		0.009***	0.012***		0.005**	0.004**
		(0.002)	(0.002)		(0.002)	(0.002)
Import Competition		0.004***	0.004***		0.002**	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
H(Daycount)	Yes	Yes	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Emergency FE	Yes	Yes	Yes	Yes	Yes	Yes
Donor FE	Yes	Yes	Yes	Yes	Yes	Yes
Emergency-Day FE	No	No	Yes	No	No	Yes
Emergency-Donor FE	No	No	No	Yes	Yes	Yes
N	3,542,509	3,221,432	3,221,432	3,542,449	3,221,371	3,221,371

Notes: Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Two-way clustered (at donor and recipient level) standard errors in parentheses. Baseline results using three-day window after decision day.

Turning to the competition hypothesis (column 2), we find that, as expected, donors' probability to follow their peers' aid decisions increases with their degree of trade competition in the disaster-affected country. In the case of fully overlapping export patterns, another donor's (first) aid commitment within the last three days increases the probability of a new donor contributing today by nearly one percentage point. Import similarity shows a similar effect, though less than half as strong. Importantly, when we account for these competition variables, the general bandwagon effect disappears entirely, indicating that donor competition—not mere imitation—drives the clustering of aid decisions. The size of the strategic competition effect becomes even larger when we include emergency-day fixed effects (column 3). One additional commitment now raises the probability of a follow-up aid decision by 1.2 (0.4) percentage points when donors share the same export (import) structure in the disaster-affected country.

In columns 4 to 6, we repeat the analysis including emergency-donor fixed effects. As the allocation decision itself is absorbed, this allows us to isolate the timing of the aid decision. Our findings continue to support the bandwagon hypothesis (column 4), which again is fully mediated by the competition variables (column 5). Notably, both the export as well as import competition effect are reduced in size. The reduction observed in column 6, relative to column 3, suggests that timing accounts for one-third of the competitive export response, while the aid allocation decision itself drives the remaining two-thirds. While the export competition parameter is statistically significant across all specifications, this is not always the case for import competition—though also positive, it is estimated imprecisely in the most demanding specification.

Taken together, these results show that commercial competition plays a crucial role in donor behavior after natural disasters. When donors exhibit similar trade patterns in recipient countries, they seem to more closely monitor and respond to each other's aid decisions. This suggests that donor countries use disaster aid strategically to maintain their commercial influence, and their export penetration in particular, in aid recipient countries.[25]

3.3 Lead Donor

To further examine the influence that donor countries exert on one another, we single out particularly influential donors that are well-positioned to steer the aid behavior of other countries. Rather than imposing a fixed set of lead donors assumed to be equally relevant across all recipient countries, we adopt Steinwand's (2015) empirical

[25]It could be the case that only *strategic* goods, such as scarce natural resources, matter in the case of securing import markets. However, re-estimating our models with an import similarity index based only on key and strategic goods yields comparable results (not reported). That is, competition over export markets continues to be the larger force responsible for speeding up emergency aid decisions. Specifically, we consider metalliferous ores and metal scrap (SITC2 28), all fuel subcategories (32, 33, 34, 35), medicinal and pharmaceutical products (54), and iron and steel (67) as strategic goods. For more information on the definition of strategic goods, see European Commission (2017).

approach. This method identifies, for every recipient country and year, whether a lead donor exists and, if so, who it is. Specifically, Steinwand (2015, p. 445) defines lead donors as those in "a long-time stable exclusive relationship" with the recipient country, "in which the donor continuously acts as biggest provider of foreign aid."

Broadly speaking, lead donors are those that typically maintain long-term bonds with recipient countries within their sphere of influence and play a widely recognized leadership role in the aid community. Therefore, they usually possess the greatest amount of local expertise and are thus able to set the pace for other donors. As Steinwand (2015, p. 445) notes, a lead donor's "relevance for overall aid policy is reflected in the fact that the international aid community often expects lead donors to shoulder a larger burden than others when dealing with problems in affected states." Since lead donors are natural first movers after natural disasters, they offer a good opportunity to observe chains of reaction by distinguishing who follows whom. Consistent with this idea, the bottom-left panel of Figure 1 shows that recipient-year-specific lead donors provide assistance significantly faster than their peers.

To empirically determine which country (if any) is the lead donor in each recipient country in a given year, we use data on official development assistance (ODA) provided by the OECD (2024)[26] and follow Steinwand (2015) by requiring that the lead donor meets all of the following five criteria: (i) the lead donor has the largest share in the recipient country's aid receipts in a given year; (ii) the lead donor has the largest share in the recipient country's aid receipts during at least five out of nine consecutive years;[27] (iii) the lead donor must not drop out of the first place (in terms of the aid share) for more than two consecutive years within this nine-year window; (iv) the share of the lead donor must be substantially larger than that of the second largest donor;[28] and (v) the lead donor must operate in a concentrated environment (i.e., the recipient country has a low donor fragmentation).[29] According to these criteria, the most frequent lead donor in our sample is the United States (33 recipient-year pairs), followed by Japan (24), Australia (15), and France (12). About 22% of the recipient-year pairs in our sample have a lead donor. Figure 2 indicates the most frequent lead donor (if any) for each recipient country during our

[26] These flows include both (gross) humanitarian assistance and all other forms of ODA.

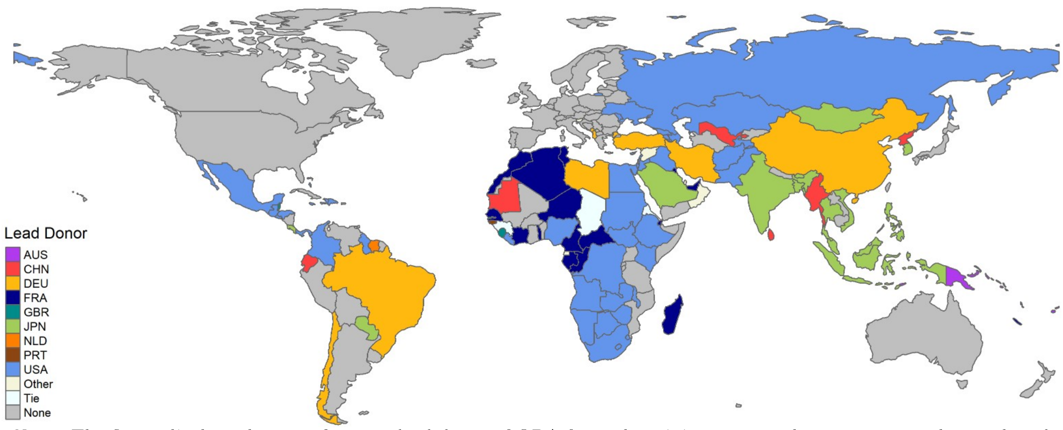
[27] This is to avoid short-term fluctuations. Steinwand (2015) argues that aid programs often last around four to five years and thus requires the lead donor to be the major aid provider in the majority of the time during approximately two aid cycles.

[28] To be precise, the difference between the top two shares must be larger than the conditional median of this difference for the subsample that satisfies the longitudinal criteria.

[29] The aid environment in a recipient-year is considered concentrated if the Hirschman-Herfindahl Index (HHI) of donor concentration is above median for the subsample that satisfies the longitudinal criteria.

sample period.

Figure 2 – Most Frequent Lead Donor by Recipient Country (2000–2022)



Notes: The figure displays the most frequent lead donor of ODA for each recipient country between 2000 and 2022, based on the definition in Steinwand (2015). Data on total (gross) ODA disbursement from OECD (2024). Donor countries listed as "other" include those that were the most frequent lead donor for less than three recipient countries, namely: Austria, Italy, Kuwait, New Zealand, Spain, Turkey, and the United Arab Emirates.

We then proceed to estimate the effect of lead donors' aid decisions on those of their peers. Following our previous model (equation 5 above), we again allow this influence to be mediated by the degree of export and import similarity between a regular donor and the lead donor. More precisely, we estimate, for donor i and lead donor j, the following equation:

$$\begin{aligned} Aid_{i,k,r,d} = \gamma_1 AidLead_{k,r,[d-3,d-1]} + \gamma_2 AidLead_{k,r,[d-3,d-1]} \times ESI_{i,j,k,r,t-1} \\ + \gamma_3 AidLead_{k,r,[d-3,d-1]} \times ISI_{i,j,k,r,t-1} + \gamma_4 ESI_{i,j,k,r,t-1} + \gamma_5 ISI_{i,j,k,r,t-1} \\ + H(Days_{i,k,r,d}) + \eta_d + \theta_d + \kappa_d + \lambda_i + \pi_{k,r} + \upsilon_{i,k,r,d} \end{aligned} \quad (6)$$

where $AidLead_{k,r,[d-3,d-1]}$ indicates whether the current lead donor in recipient country r committed to assist within the previous three days. $ESI_{i,j,k,r,t-1}$ and $ISI_{i,j,k,r,t-1}$, as defined above, capture the similarity in export and import structure with respect to recipient country r in year $t-1$, but now between donor i and lead donor j.

The results in panel A of Table 3 show that lead donors exert considerable influence over their peers. Even before taking competition into account (column 1), we find that the decision of a lead donor to provide assistance makes it more likely that other donors will follow suit in the following days. This provides additional support for the bandwagon hypothesis—although, as before, the coefficient loses significance once the interaction terms are included. In line with the previous results, the impact on aid decision is driven by export competition (column 2) and is robust to the inclusion of both emergency-day fixed effects (column 3) as well emergency-donor fixed effects (columns 4 and 5). A lead donor's aid commitment within the last three days makes it up to 2.8 percentage points more likely that a donor country with an identical export structure (in a given affected country) also decides to provide aid. However, in contrast to the results for all peers reported above, we do not find import competition to be a significant driver of the bandwagon effect in this case.

Summing up, we find that lead donors accelerate their peers' aid commitments and that this effect is more pronounced if donors compete over export markets in the disaster-affected country. Remarkably, the export competition with the lead donor prevails even over the competition with all other donors combined, as columns 6 and 7 indicate.

Table 3 – Lead Donor

	Dependent Variable: *Aid*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A – Lead Sample			
Aid Lead	0.004**	-0.004		-0.002			
	(0.002)	(0.003)		(0.001)			
ESI * Aid Lead		0.025**	0.028***	0.014**	0.013**	0.016*	0.012*
		(0.011)	(0.010)	(0.006)	(0.005)	(0.009)	(0.006)
ISI * Aid Lead		0.008	0.006	0.005	0.002	0.002	0.002
		(0.008)	(0.010)	(0.005)	(0.007)	(0.010)	(0.008)
Export Competition						0.007	0.001
						(0.004)	(0.003)
Import Competition						0.003	-0.000
						(0.002)	(0.002)
N	752,156	651,072	651,072	651,063	651,063	651,072	651,063
				Panel B – Full Sample			
Aid Lead	0.004*	-0.003		-0.001			
	(0.002)	(0.002)		(0.001)			
ESI * Aid Lead		0.023**	0.025**	0.012*	0.011*	0.009	0.007
		(0.010)	(0.010)	(0.007)	(0.006)	(0.009)	(0.006)
ISI * Aid Lead		0.007	0.005	0.005	0.001	0.001	0.000
		(0.007)	(0.009)	(0.006)	(0.007)	(0.010)	(0.007)
Export Competition						0.012***	0.004**
						(0.002)	(0.002)
Import Competition						0.004***	0.001
						(0.001)	(0.001)
N	3,531,137	3,531,137	3,531,137	3,531,079	3,531,079	3,210,100	3,210,041
H(Daycount)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Emergency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Donor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Emergency-Day FE	No	No	Yes	No	Yes	Yes	Yes
Emergency-Donor FE	No	No	No	Yes	Yes	No	Yes

Notes: Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Two-way clustered (at donor and recipient level) standard errors in parentheses. Baseline results using three-day window after decision day. When some interaction term with a similarity index is included, then the specification also controls for the similarity index separately.

Panel A includes only emergency-recipient pairs where the recipient country has a lead donor at the time of the disaster—which is the case for about a quarter of the emergencies. While this subset is of particular interest, it is not necessarily representative of the universe of fast-onset natural disasters that occurred between 2000 and 2022. Therefore, panel B repeats the specifications from panel A using the full sample. The conclusions from columns 1 to 5 are fairly similar: lead donors continue to influence the aid decision of other donors, primarily through export competition. Columns 6 and 7, however, indicate that, unlike in panel A, the lead donor effect no longer dominates. This suggests that while lead donors exert substantial influence within their respective spheres—sometimes even more than all other donors combined—, this effect gets blurred when considering the broader set of disaster events. Altogether, these results show that the decisions of lead donors considerably affect the aid strategy of their peers. As such, lead donors can play an important role to mobilize disaster relief, which is particularly important to support underfunded emergency appeals.

3.4 G7 and "Good" Donors

Expanding on our assessment of certain important individual donors, we now proceed to analyze two specific sets of countries. First, we replicate the analysis introduced above for G7 countries. Like lead donors, G7 nations are among the most influential aid providers and, given their economic weight, are arguably more likely to use aid as a tool to advance their own agendas and may thus be more likely to prompt other donors to react.[30] However, unlike lead donors, which are recipient-specific, the influence that G7 countries exert should be more widespread. In other words, we expect these countries to be relevant in more settings, although the degree to which they matter may be smaller than that of lead donors in their areas of influence. As Appendix Table A3 shows, we find evidence in support of the competition hypothesis for five of the seven countries: Canada, France, Germany, Japan, and the United States. What is more, the magnitude of this effect is comparable to that observed in the analogous specification for lead donors.[31]

Second, we present results for a group of so-called "good" donors—Denmark, Netherlands, Norway, and Sweden—, which "traditionally see poverty alleviation as the main objective of their aid giving" rather than their own interest (Neumayer,

[30]We use the specification with emergency-donor but without emergency-day fixed effects to ensure that we can still estimate the bandwagon parameter.

[31]There is of course a considerable overlap between the two groups as G7 countries are often prominent lead donors.

2003, p. 658).[32] Hence, unlike lead donors and G7 countries, in this case we expect significantly lower levels of competition. In fact, our results provide hardly any evidence of it vis-à-vis these "good" donors (Appendix Table A4). The coefficients on the interaction between Aid and ESI are consistently positive but very small and only turn weakly significant for the Netherlands—the only country among the "good" donors which is classified as a lead donor. However, and perhaps surprisingly given the positive reputation that these donors enjoy among their peers, we also do not see any sign that the aid decision of these donors, by itself, attracts additional donors, as indicated by the insignificant coefficient on Aid.

Finally, we estimate how donor countries react to the aid decision of each individual donor in our sample. Most donors (28 out of 43) seem to be able to generate a bandwagon effect on their peers—and in no case is there any evidence of a negative, that is, crowding-out effect (Appendix Figure A5). The strategic competition effect, however, is limited to a much smaller set of countries (Appendix Figure A6), suggesting that only a few donor countries are influential—and perhaps economically important—enough to trigger competitive responses from their peers. In terms of export competition, these include major trading countries like China, Germany, and Japan.

4 Robustness

We run additional regressions to test the robustness of the evidence supporting the bandwagon and commercial competition hypotheses. In what follows, we use our preferred specification with emergency-donor fixed effects as baseline. In the case of specifications related to the competition hypothesis, we show, in addition, the stricter regressions that include also emergency-day fixed effects for comparison.

First, the choice of a three-day response window used above might appear arbitrary. Replacing it by a one-day (Table 4, columns 1 and 2) or a one-week window (columns 3 and 4) does not change our baseline findings, both with respect to the bandwagon effect as well as export competition. Both effects are larger when we apply the shorter one-day window, indicating a stronger crowding-in effect in the immediate aftermath of another donor's aid decision. The coefficient size of $ImpComp$ is stable across windows but differs in precision. In the case of a one-week window, the import competition also becomes statistically significant at the 1% level.[33]

Second, the probability of a donor country to assist others may vary throughout

[32] We do not include Canada as a "good" donor because it is also part of the G7.

[33] Using different time windows (not shown), ranging from one up to ten days, yields comparable results.

the fiscal year (Eichenauer, 2020). For instance, at the end of budget years, countries may be particularly inclined to spend whatever is left and, therefore, provide emergency relief. To make sure that patterns, such as year-end spending spikes, do not get in the way of our analysis, we repeat our preferred specification (column 6 in Table 2), but now including also donor-month fixed effects—given that the fiscal year may vary from country to country. As column 5 in Table 4 indicates, the coefficients of interest barely change.

Third, a critical reader might argue that our measures of commercial similarity could actually be picking up dimensions of similarity other than competition and therefore just proxying for the underlying (unobserved) affinity between donors. An important concern is that not all donors may receive information about disaster impact at the same time, and thus one could expect that more similar donors receive these news at more similar frequencies. If commercial similarity happens to be correlated with information transmission between countries, our results could be spurious.

Table 4 – Bandwagon and Competition: Robustness

	Dependent Variable: *Aid*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No. of donors (1d)	0.003***						
	(0.001)						
Export Competition (1d)		0.007**					
		(0.004)					
Import Competition (1d)		0.001					
		(0.002)					
No. of donors (7d)			0.001***				
			(0.000)				
Export Competition (7d)				0.004***			
				(0.001)			
Import Competition (7d)				0.001***			
				(0.000)			
Export Competition					0.004**	0.004**	0.005**
					(0.002)	(0.002)	(0.002)
Import Competition					0.001	0.001*	0.002*
					(0.001)	(0.001)	(0.001)
Information						-0.001	
						(0.000)	
Geopolitical Alignment							-0.001
							(0.001)
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Emergency-Donor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Emergency-Day FE	No	Yes	No	Yes	Yes	Yes	Yes
Donor-Month FE	No	No	No	No	Yes	No	No
N	3,542,449	3,221,371	3,542,449	3,221,371	3,221,371	3,221,371	3,204,847

Notes: Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Two-way clustered (at donor and recipient level) standard errors in parentheses. Baseline results using three-day window after decision day. Columns 1 to 4 show results for two alternative time windows, one (1d) and seven days (7d).

To account for this potential source of bias, we construct an information similarity index ($InfoSI$) based on the difference in informational globalization levels between donors i and j: $\Delta KOFI_{i,j,t} = |KOFI_{i,t} - KOFI_{j,t}|$, where $KOFI$ is the informational component of the KOF Index of Globalization (Dreher, 2006; Gygli et al., 2019). It combines measures of *de facto* and *de jure* informational globalization, such as internet bandwidth and press freedom, which should affect how fast disaster news arrive in a country. We then normalize $\Delta KOFI_{i,j,t}$ to obtain an index, $InfoSI_{i,j,t}$, that varies between zero and one.[34]

We expect a pair of countries with a high $InfoSI$ to obtain new information about a given disaster at more similar times. Finally, we aggregate it over the donors that committed to assist within the previous three days to construct $Info$, which we include as a control variable in column 6 (Table 4).[35] If the informational channel is spuriously driving our results, it should dominate and render $ExpComp$ and/or $ImpComp$ insignificant.

Reassuringly, the effect of commercial competition remains very similar in terms of size, although less precisely estimated. This provides additional support to our interpretation that donors are not moving in sync because they simply receive disaster information at similar times, but are rather speeding up in response to other donors they see as potential export—and, to a lesser extent, import—competitors in a given recipient country.

Fourth, another important dimension is geopolitical alignment. On top of being important on its own—as we show in Section 2—geopolitical interest may also be correlated with commercial disputes.[36] As such, one might argue, for instance, that if donor countries with a similar export structure are, for whichever reason, more geopolitically aligned, we could falsely attribute our previous results to commercial competition rather than geopolitical motivations. To rule out this possibility, we employ a commonly used indicator of geopolitical alignment, based on voting at the United Nations General Assembly, to create a geopolitical similarity index, which we call GSI (e.g., Thacker, 1999; Kilby, 2009; Dreher et al., 2008). Similarly to the commercial measures introduced previously, we then aggregate GSI into $GeoAlign$. Note that, differently from the approach used to assess geopolitical alignment in Section 2 (between donor and recipient), we now use the ideal-point distance between pairs of donors, i.e., $\Delta UNGA_{i,j,t} = |idealpoint_{i,t} - idealpoint_{j,t}|$ (data from Bailey

[34]That is, $InfoSI_{i,j,t} = \frac{-\Delta KOFI_{i,j,t} - Min(-\Delta KOFI_{i,j,t})}{Max(-\Delta KOFI_{i,j,t}) - Min(-\Delta KOFI_{i,j,t})}$.

[35]In line with ESI and ISI, we use one-year lagged $InfoSI$ values.

[36]Because geopolitical similarity *between donors* does not seem matter on its own—that is, it is insignificant even when it is included in a specification without the commercial similarity variables (not reported)—, in this part of the analysis we focus on the threat posed by it being a potential confounder.

et al. 2017). Finally, we normalize this variable such that the index ranges from zero to one. The more similar the votes cast by donor countries i and j in year t are, the higher the index.[37]

As previously discussed, and differently from our measures of export and import similarity, the implications of donor countries having more similar foreign-policy preferences are not straightforward. Whereas a positive *GeoAlign* coefficient would indicate that donors are more likely to follow the leadership of important countries if they are politically aligned—and thus signal cooperation—, a negative coefficient could be evidence of donor competition fueled by geopolitical rivalries. The net effect is thus an empirical question.

As can be seen in column 7 in Table 4, the coefficient for *GeoAlign* is a rather precisely estimated zero, which could indicate that the positive and negative forces described above cancel each other out. Most importantly, our main finding of export and import competition speeding up emergency aid is largely unaffected by the inclusion of *GeoAlign*.

Fifth, with regard to the measures of commercial competition, *ExpComp* and *ImpComp*, although long established in the literature (Finger and Kreinin, 1979; Fuchs et al., 2015; Asmus-Bluhm et al., 2025), one concern is that they do not take the trade *volume* into account. That is, donors may have similar sectoral shares of goods exported to or imported from particular recipient countries, while substantially differing in terms of the absolute value traded. To account for this issue, we adjust the two similarity indices (before the aggregation) by multiplying each of them with the logged traded amount—exports ($X_{i,r,t-1}$) or imports ($M_{i,r,t-1}$)—between donor i and recipient r in year $t-1$. We then use the same aggregation method, described in equations 3 and 4, to calculate these adjusted measures, $ExpComp^{Adj}$ and $ImpComp^{Adj}$:

$$ExpComp^{Adj}_{i,j,r,k,[d-3,d-1]} = \sum_j Aid_{j,k,r,[d-3,d-1]} \times ln(X_{i,r,t-1}) \times ESI_{i,j,r,k,t-1} \tag{7}$$

$$ImpComp^{Adj}_{i,j,r,k,[d-3,d-1]} = \sum_j Aid_{j,k,r,[d-3,d-1]} \times ln(M_{i,r,t-1}) \times ISI_{i,j,r,k,t-1} \tag{8}$$

As Appendix Table A5 shows, our conclusions remain unchanged. The more donors' exports and imports overlap, also when the traded amount is taken into

[37] More precisely, $GSI_{i,j,t} = \frac{-\Delta UNGA_{i,j,t} - Min(-\Delta UNGA_{i,j,t})}{Max(-\Delta UNGA_{i,j,t}) - Min(-\Delta UNGA_{i,j,t})}$.

account, the faster donors respond to each other, which we interpret as evidence of commercial competition.

Sixth, we rerun our baseline specifications for the bandwagon as well as the competition hypotheses, but each time excluding one sample year or donor. Appendix Figures A7 and A8 show that our results are not driven by a single year or donor, respectively. We obtain statistically significant coefficients of similar magnitude.

Finally, we use the lead donor setting to conduct a "placebo test." To increase our confidence that we are indeed identifying the influence that these donors have over their peers and address concerns about spurious correlation, we code placebo aid decision variables that pretend that the lead donor decided to provide assistance *before* it has actually done so—in a window that stretches back in time from one day prior to the actual decision date ($dd-1$) up to five days in the past ($dd-5$). In line with expectations, we observe no significant effects when we look at the placebo coefficients, which thus strengthens the argument that the lead donor is indeed leading other donors—and not being led. Accordingly, it is only *after* the lead donor's commitment (from $dd+1$ onward) that the effect becomes significant—although, as expected, it wanes the further the window stretches in time.[38] Figure 3 plots the main coefficient of interest, $ESI \times AidLead$, for each of these specifications.

5 Mechanisms

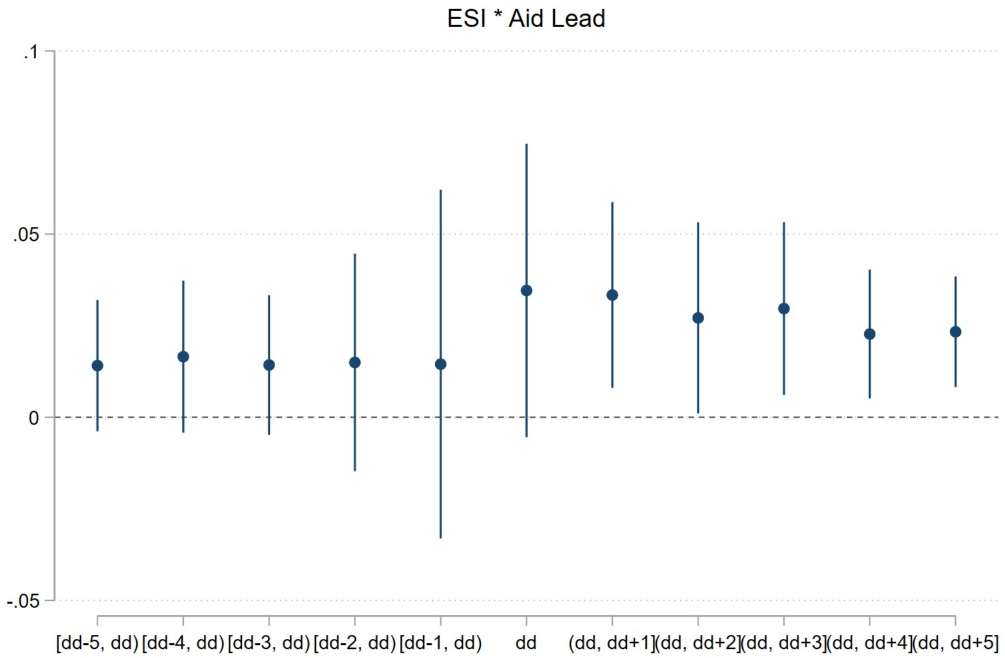
In what follows, we examine two important factors that drive the bandwagon effect as well as commercial competition between donors. First, we investigate the role of different types of humanitarian aid and the way in which it is channeled. Second, we devote our attention to the severity of each disaster to shed more light on donors' motivations.

5.1 Aid Channel and Type

Donor countries must choose through which channel their aid is funneled and the type of assistance they provide—financial or in kind. Channels include direct transfers to recipient governments or indirect deliveries through multilateral and international organizations (IOs), such as UN agencies, non-governmental organizations (NGOs), and member organizations of the International Federation of Red Cross

[38]Note that, except for the specification that measures the response to the lead donor's decision day (dd) itself, the other models are based on time windows that do not include the decision day. This is consistent with our baseline strategy, which makes use of a window ranging from one to three days after the aid decision and thus does not include the day on which the decision was taken.

Figure 3 – Lead Donors: Various Reaction Windows (ESI × Aid Lead)



Notes: The figure shows the coefficient for ESI × Aid Lead from different regressions. These are based on the specification in column 3 in Table 3 (panel A), but each with a different time window. As indicated on the horizontal axis, these include a window containing only the decision date (*dd*) itself as well as intervals ranging from the decision date (open interval) up to five days prior or after the actual decision date (closed interval). Regressions include donor, and emergency-day fixed effects. The figure shows 95% confidence intervals.

and Red Crescent Societies (IFRC). As acknowledged by the aid allocation literature (e.g., Cassen, 1986; Dollar and Levin, 2006; Raschky and Schwindt, 2012), these choices too are likely shaped by donors' strategic interests and reflect, among other considerations, the extent of discretion and flexibility entrusted to recipient countries. In particular, there is evidence that "[d]onors are more likely to give bilateral transfers/cash transfers to countries where they want to promote strategic or political interests" (Raschky and Schwindt, 2012, p. 112). This is because these are typically the modalities that come with fewer restrictions on use and implementation. Therefore, if donors are competing with one another with the goal of maximizing goodwill with the recipient government and hence help secure their commercial interests, we should expect them to choose the channel and type that are more likely to please its beneficiary. That is, if a donor country wishes to stave off some commercial competitor who recently committed to assist, it is more likely to be successful if it engages directly with the recipient country.[39] The choice of the type of aid, however, seems to be less straightforward, as we will discuss below.

[39]Differently from the competition hypothesis, the bandwagon effect does not have clear implications for the choice of aid type and channel. Therefore, in this part, we focus on the strictest specification (with emergency-day fixed effects), in which case we are not able to identify the bandwagon parameter.

Starting with aid channel, specifications in columns 1 to 4 in Table 5 are a variant of our baseline model with emergency-day and emergency-donor fixed effects, in which we replace our dependent variable by a binary variable that indicates whether donor country i on day d decides to provide humanitarian assistance to recipient country r in response to disaster k through the following implementing organizations: recipient government (column 1), IFRC (column 2), IOs (column 3), or NGOs (column 4).

Consistent with the argument that donor countries are competing against each other to please recipient countries that are important trade partners, we observe that our result of commercial competition is indeed driven by government-to-government aid, i.e., the channel usually preferred by recipient governments as this gives them direct control of the funds and goods received (column 1). Furthermore, also in line with our expectations, when donor countries opt to provide emergency aid via non-state actors, commercial competition does not seem to influence their decision (columns 2 to 4). In fact, donor countries may choose these options precisely because they wish to bypass certain recipient governments (Acht et al., 2015).

While these results for aid channels are in line with our expectations, the results for aid types in columns 5 and 6 are, at first glance, puzzling. We find that the strategic competition effect is only statistically significant, at conventional levels, for in-kind aid.[40] A potential explanation is that, although one could expect attempts to curry favors with local governments to be made predominantly via financial aid (as in Raschky and Schwindt, 2012), in-kind aid may also be used in cases in which it is the most effective—and thus arguably also the one preferred by recipient countries in distress. This is consistent with the fact that the share of in-kind aid is higher for more severe natural disasters.[41] Therefore, in some cases what pleases recipient governments the most may simply be what is most effective in terms of addressing the pressing needs that arise in the aftermath of natural disasters. Importantly, the observed effect on *financial* assistance, though marginally insignificant, helps rule out an alternative explanation: that donors with similar export structures simply follow each other because they share similar logistical networks in recipient countries.

[40]Testing the statistical significance of the *ExpComp* coefficient for financial aid (column 5) yields a p-value of 0.118.

[41]Dividing the sample by the median number of people killed in each disaster, the share of in-kind flows is 22% for the bottom half of the distribution, but 26% for the upper half—and rises to 32% for the upper quartile.

Table 5 – Aid Channel and Type: Competition

	Dependent Variable: *Aid*					
	(1)	(2)	(3)	(4)	(5)	(6)
Export Competition	0.002**	0.001	-0.000	0.000	0.002	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Import Competition	0.001*	-0.000	-0.000	0.000	0.000	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Emergency-Donor FE	Yes	Yes	Yes	Yes	Yes	Yes
Emergency-Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Channel/Type	Govt-Govt	Govt-IFRC	Govt-IO	Govt-NGO	Financial	In Kind
N	3,221,371	3,221,371	3,221,371	3,221,371	3,221,371	3,221,371

Notes: Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Two-way clustered (at donor and recipient level) standard errors in parentheses. Baseline results using three-day window after decision day. The table shows results for bilateral humanitarian aid provided to different implementing agents—recipient government (Govt), the International Federation of Red Cross and Red Crescent Societies (IFRC), multilateral and international organizations (IO), and non-governmental organizations (NGO)—as well as for different aid types, financial and in kind.

5.2 Disaster Severity

Donors may react differently depending on how severe natural disasters are. In particular, disaster severity may tilt the balance between humanitarian and strategic objectives one way or another. On the one hand, more severe emergencies may reduce donors' ability to act strategically with their aid timing. When faced with large disasters, they are more likely to respond fast regardless of which other donors are moving before them. In other words, donors might have less room for "strategic urgency." This is not to say that this urgency is driven purely by altruistic motives—media attention, for instance, may propel aid providers to act (Eisensee and Strömberg, 2007)—but it is then not primarily driven by competition with other donors. Minor emergencies, on the other hand, are generally less relevant and salient also for the affected countries, such that the behavior of donors is arguably less scrutinized in these cases. Therefore, we expect medium-scale disasters to offer the most room for strategic considerations: they are significant enough to warrant attention but not so devastating such that most donors have basically no alternative but to act fast.

To examine whether this is the case, we rerun our preferred specification across different levels of disaster severity, dividing our sample into quintiles based on the death toll of each emergency. In line with our argument above, Table 6 shows that export competition occurs primarily in settings of medium severity (second and third quintiles). The number of deaths in these emergencies ranges from 18 to 275.

We also test the bandwagon hypothesis across quintiles of disaster severity, again excluding emergency-day fixed effects for obvious reasons. We find the bandwagon effect to be robust across the severity distribution, intensifying threefold in the most

Table 6 – Disaster Severity: Competition

	Dependent Variable: *Aid*				
	(1)	(2)	(3)	(4)	(5)
Export Competition	0.001	0.005*	0.006***	0.000	0.006
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Import Competition	-0.001	0.002	-0.000	0.002	0.002
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Emergency-Day FE	Yes	Yes	Yes	Yes	Yes
Emergency-Donor FE	Yes	Yes	Yes	Yes	Yes
Quintile	Q1	Q2	Q3	Q4	Q5
N	609,632	597,052	589,310	581,162	477,026

Notes: Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Two-way clustered (at donor and recipient level) standard errors in parentheses. Baseline results using three-day window after decision day. The quintiles of disaster severity are calculated based on the death toll of each emergency.

severe disasters (Appendix Table A6). This indicates that, while the the strategic competition effect is limited to mid-sized catastrophes, donors seem to consistently take cues from their peers and the bandwagon effect amplifies dramatically when stakes are highest.

6 Conclusion

Although the allocation of emergency relief has been extensively studied (e.g., Eisensee and Strömberg, 2007; Strömberg, 2007; Fink and Redaelli, 2011; Raschky and Schwindt, 2012), far less attention has been given to one of the most critical determinants of its effectiveness: the speed of aid. Our analysis reveals substantial variation in how quickly donor countries respond to fast-onset natural disasters, providing new evidence that these differences are influenced by strategic motives alongside humanitarian considerations. Specifically, we find that close trade partners receive faster assistance.

Moreover, the results from our empirical analysis at the daily level highlight the powerful influence that donors have on each other. On the one hand, we observe a bandwagon effect: whenever donors decide to provide assistance, they encourage their peers to quickly follow suit. In the context of humanitarian relief, this shows that certain donors can play an important role to improve the speed—and thus the effectiveness—of aid provision. On the other hand, our findings indicate that the extent to which donors respond to other aid providers is mediated by their own agendas, and in particular by an effort to secure their export markets and, to a lesser extent, the source of their imports. The more donors compete, commercially, over a given recipient country, the faster they respond to each other. Consistent with the expectation that the choice of aid channel is endogenous to donors' motivations, our findings are driven by government-to-government aid.

While one could naïvely conclude that commercial competition could end up being beneficial as it induces donors to act faster, there are at least three important caveats. First, assistance motivated by donors' own commercial goals is arguably less effective than a pure need-based approach.[42] Second, based on the ethical principles of humanitarian law, emergency aid has been devised as a tool to provide quick relief to countries in distress and, to a much greater extent than development aid, is often advertised as being altruistic (Drury et al., 2005). As our results indicate, however, this is not what happens in practice. This is likely to thus (further) erode donor credibility and create even more obstacles for a coordinated response. Third, to the extent that donor competition fuels aid fragmentation, it further compromises the effectiveness of emergency relief, in particular—in the case of humanitarian aid—by overburdening recipient bureaucracies at times of great vulnerability.[43]

We acknowledge several limitations and avenues for future research. First, we do not examine actual delivery date and focus rather on commitment dates. Although aid commitments are legally binding and arguably the most relevant variable from a strategic point of view, once comprehensive data become available, expanding the analysis to include the day on which aid flows arrive at the disaster-affected area would further improve our understanding about the implications for aid effectiveness. Second, future research on emergency aid should put more emphasis on how aid requests from disaster-affected countries affect donor response, as recipient behavior is an important part of the donor decision to provide aid (Carnegie and Dolan, 2021). Third, future studies on emergency aid could compare the speed with which donor countries respond with that of international organizations and private donors. This is particularly relevant given the evidence that the United Nations adheres to its core principles of neutrality, impartiality, and independence in disaster aid allocation (Dellmuth et al., 2021). Finally, although a speedy decision-making process is an important prerequisite for (most types of) disaster aid to be successful, a fast response following a disaster is not the only objective of emergency assistance. Disaster preparedness, for example, should be an important part of humanitarian

[42]One strand of the aid literature argues that donor motives matter for aid effectiveness (Kilby and Dreher, 2010; Dreher et al., 2013; Dreher et al., 2018).

[43]There is plenty of evidence of the detrimental consequences of donor fragmentation. See, for example, Easterly (2007), Knack and Rahman (2007), Djankov et al. (2009), and Gutting and Steinwand (2017)—though Gehring et al. (2017) disagree. However, on the positive side, fragmentation may also reduce the likelihood of negative aid shocks and hence of violent conflicts in recipient countries (Nielsen et al., 2011; Strange et al., 2017). While this potentially beneficial aspect should not be neglected, it is much less relevant for emergency assistance than for general development assistance.

aid activities (Clarke and Dercon, 2016). To the extent to which a long decision time stems from aid coordination efforts among donors, donors should not be solely judged on their aid promptness. Beyond the timeliness of the aid decision, future research should evaluate the effectiveness of disaster aid efforts more broadly, the study of which is currently largely confined to country case studies.

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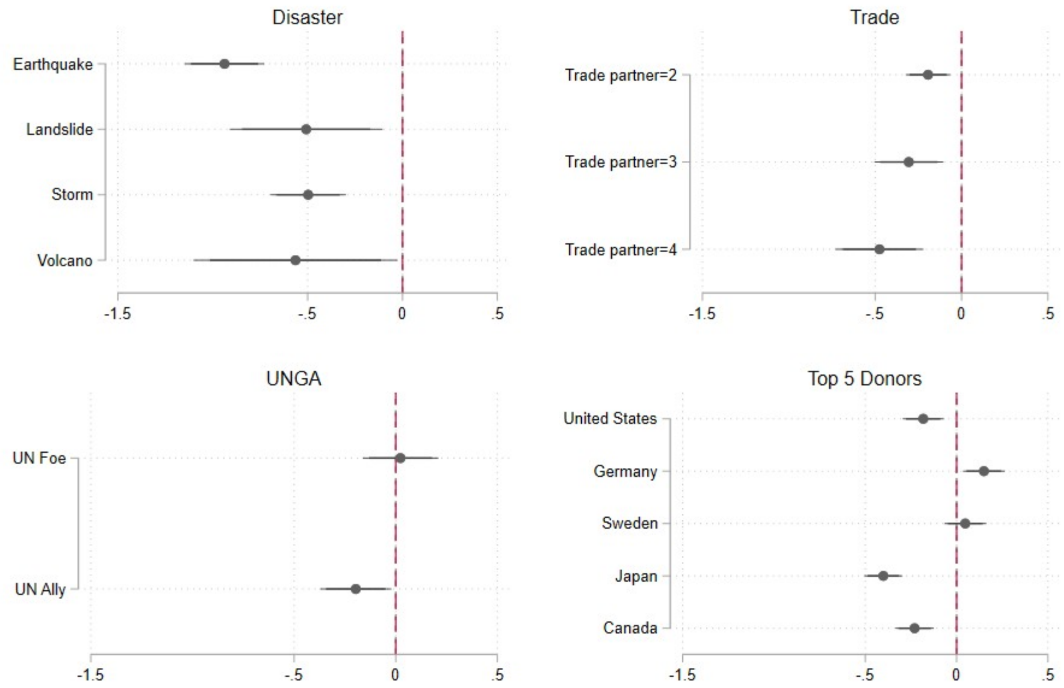
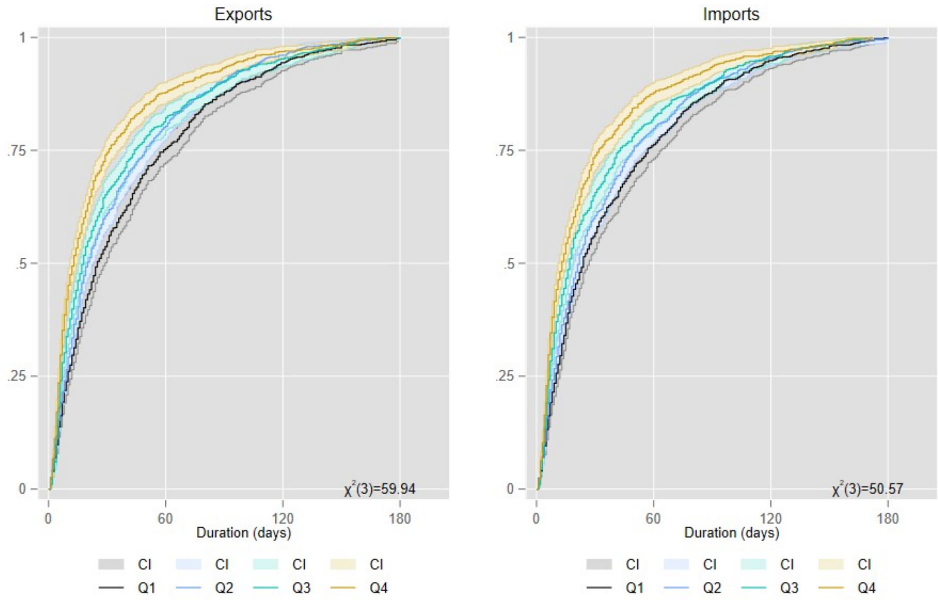
Appendix

Figure A1 – Coefficient Plots: Disaster Type, Bilateral Determinants, and Top 5 Donors



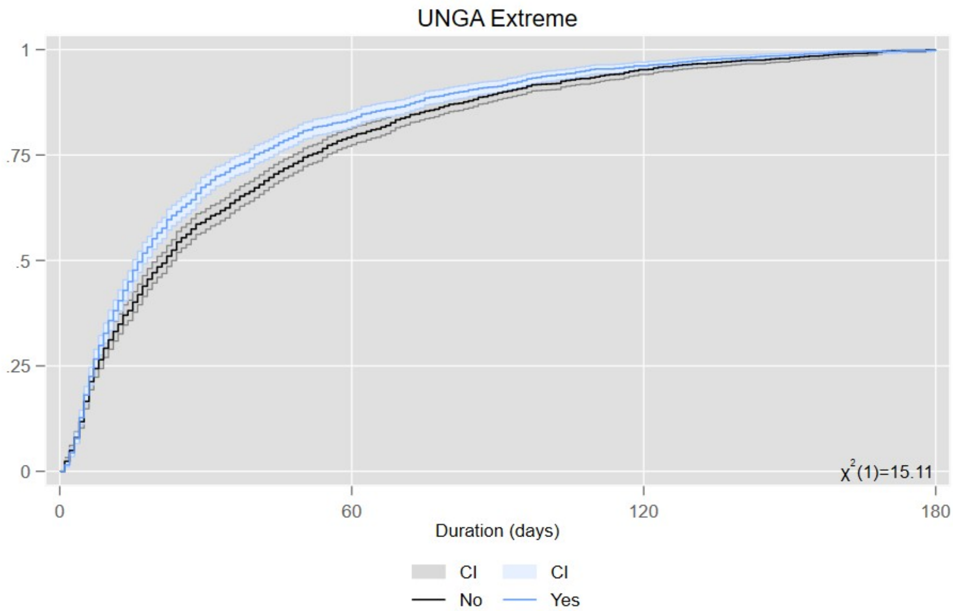
Notes: Top-Left: Binary variables for each disaster type (earthquake, landslide, storm, volcano and flood). Flood is the omitted category. Model controls for the logarithm of number of people killed, the logarithm of number of people affected, recipient lagged logarithm of GDP per capita, and recipient lagged logarithm of population, and includes donor-recipient and year fixed effects. *Top-Right*: Binary variables for each quartile of the distribution according to the total value of trade (exports and imports) between donor and recipient. First quartile is the omitted category. Model controls for the logarithm of number of people killed, the logarithm of number of people affected, recipient lagged logarithm of GDP per capita, and recipient lagged logarithm of population, and include donor, recipient and year fixed effects. *Bottom-Left*: UN Foe (UN Ally) is a binary indicator of whether a donor-recipient pair is in the fourth (first) quartile of the distribution according Model controls for the logarithm of number of people killed, the logarithm of number of people affected, recipient lagged logarithm of GDP per capita, and recipient lagged logarithm of population, and include donor, recipient and year fixed effects. *Bottom-Right*: The model includes dummy variables for each of the top five donor countries in terms of the number of aid provisions in the sample (United States, Germany, Japan, Sweden, and Canada), and controls for the logarithm of number of people killed, the logarithm of number of people affected, recipient lagged logarithm of GDP per capita, recipient lagged logarithm of population, as well as recipient, year, and disaster-type fixed effects. In all panels, the dependent variable is *Duration*. Two-way clustered (at donor and recipient level) standard error. Figure shows 90% and 95% confidence intervals.

Figure A2 – Failure Function: Exports and Imports



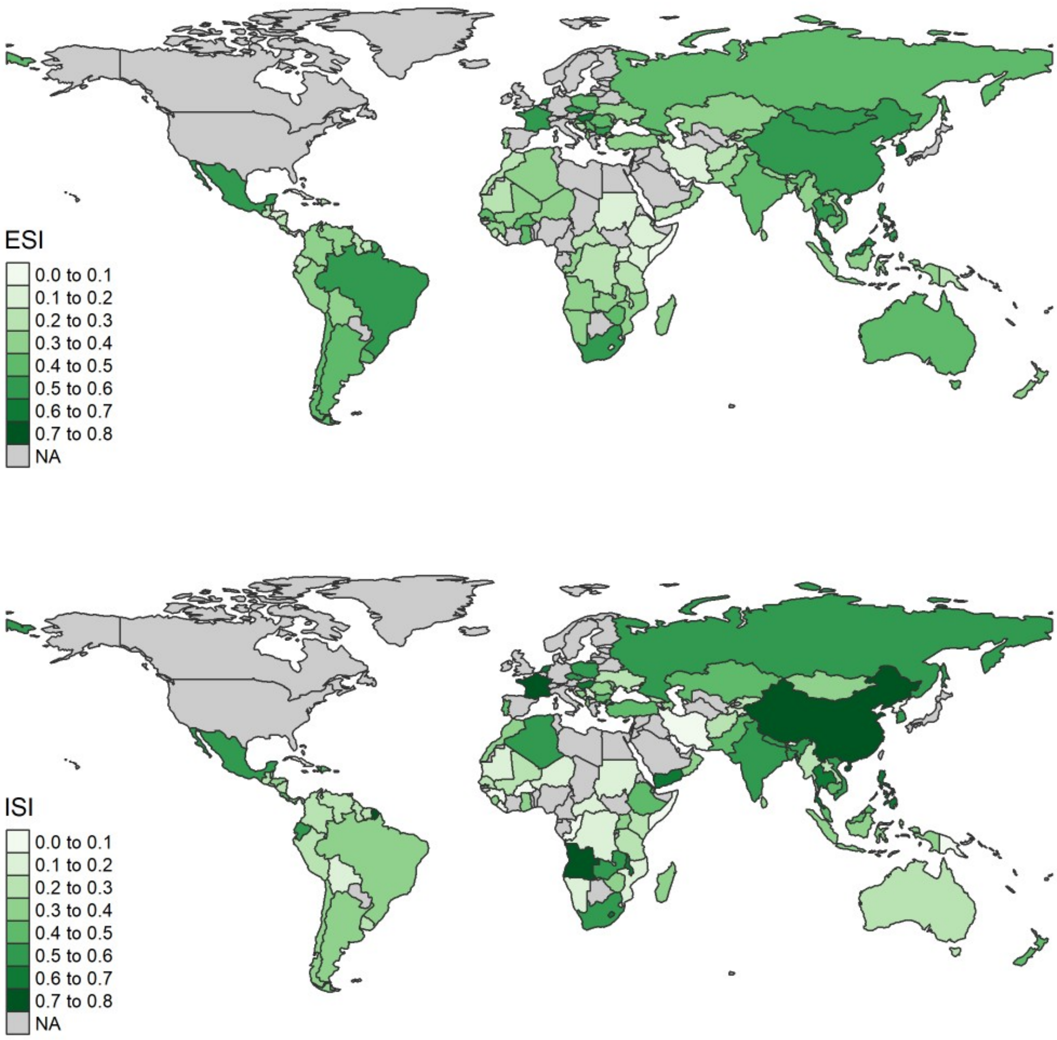
Notes: Kaplan-Meier failure functions according to donor exports (left) and imports (right) to/from the recipient country. Donor-recipient pairs are assigned to quartiles based on total value of exports and imports, respectively. Figure shows 95% confidence intervals.

Figure A3 – Failure Function: UNGA Extremes



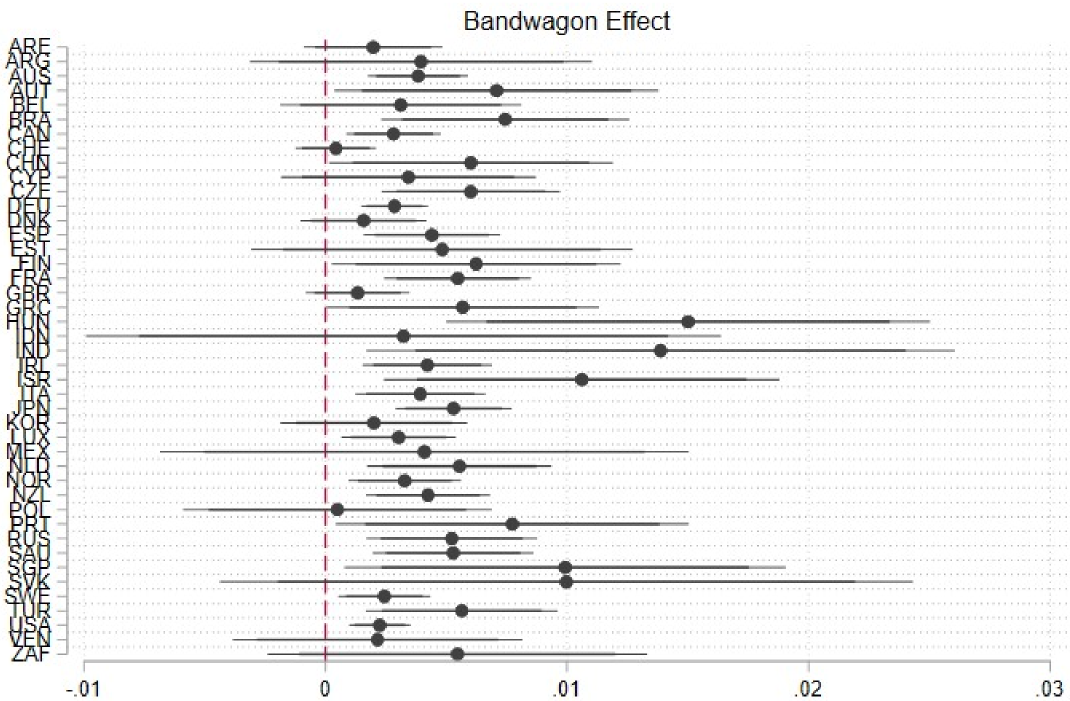
Notes: Kaplan-Meier failure functions according to UNGA voting. Donor-recipient pairs are assigned to trade and UNGA voting quartiles based on $\Delta UNGA$. The first and fourth quartiles are coded as extremes, while quartiles two and three are not. Figure shows 95% confidence intervals.

Figure A4 – Export and Import Similarity Indices of Japan and the United States (2000–2021 Average)



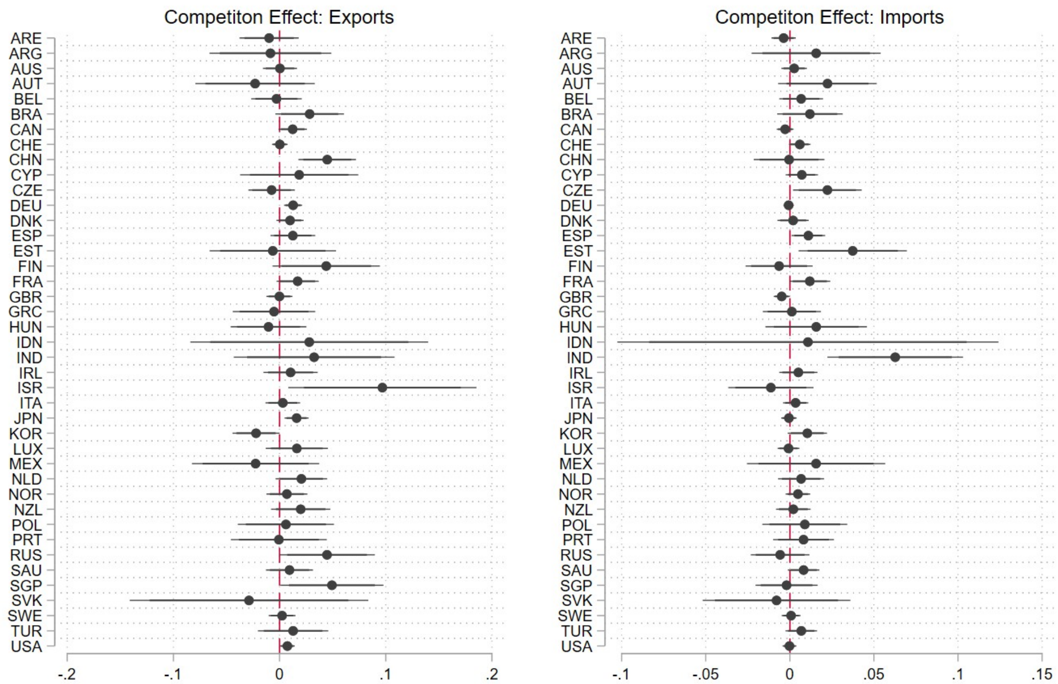
Notes: The figure shows the average export (ESI, top) and import (ISI, bottom) similarity indices between Japan and the United States between 2000 and 2021 for each recipient country. See Section 3 for details on how these indices are calculated. Authors' calculations based on data from Growth Lab (2024).

Figure A5 – Reaction to Individual Donors: Bandwagon



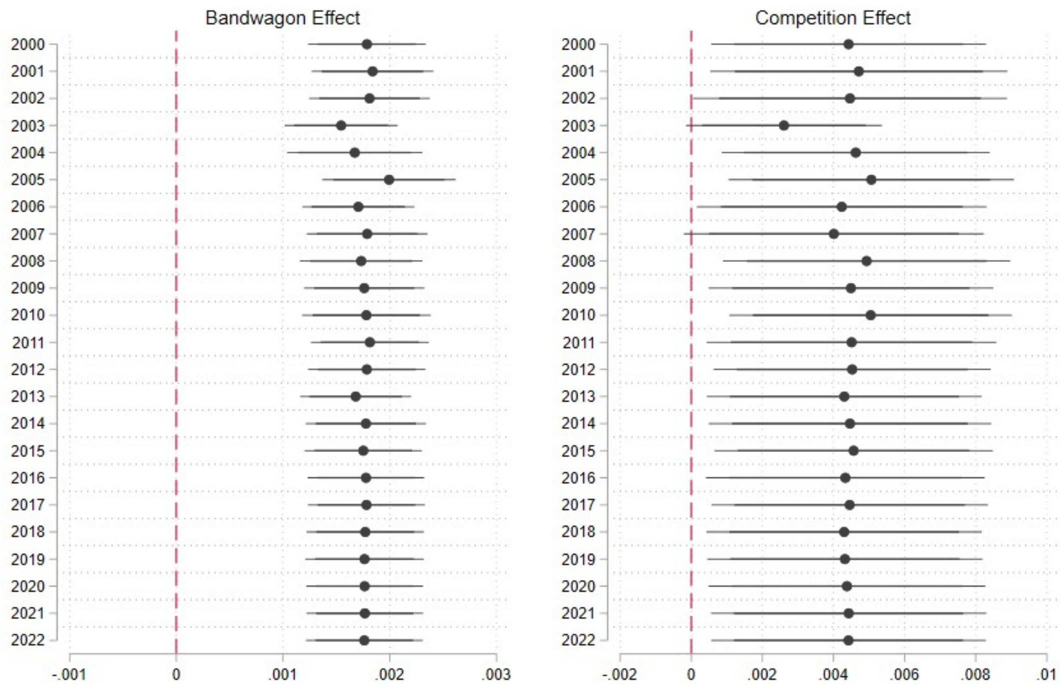
Notes: The bandwagon effect refers to the coefficient on the number of donors who decided to donate in the following three days after the donor country indicated. The specification includes emergency-donor fixed effects. The figure shows 90% and 95% confidence intervals.

Figure A6 – Reaction to Individual Donors: Competition



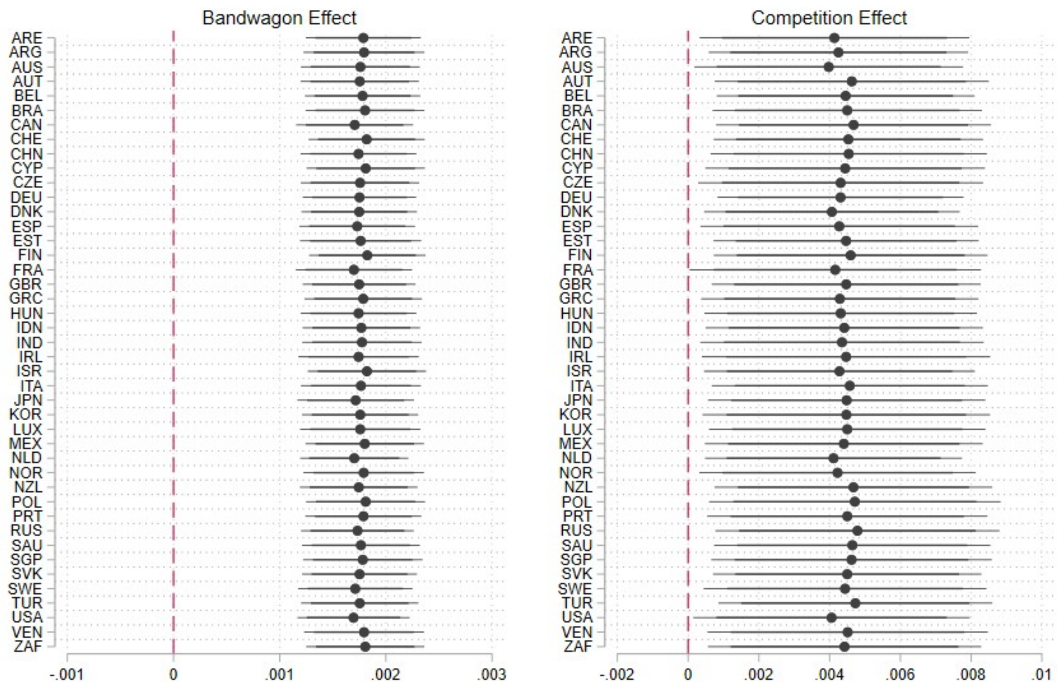
Notes: The strategic competition effect refers either to the coefficient associated with $ExpComp$ (exports) or $ImpComp$ (imports) in response to the aid decision of the donor country indicated. The window of response follows the baseline specification of three days. The specification includes emergency-donor fixed effects. The figure shows 90% and 95% confidence intervals.

Figure A7 – Robustness: Excluding Years



Notes: The bandwagon effect refers to the coefficient on the number of donors who decided to donate in the previous three days. The specification includes emergency-donor fixed effects. The strategic competition effect refers to the coefficient associated to the *ExpComp* coefficient, also relative to the previous three days, in a specification with emergency-donor and emergency-day fixed effects. The figure shows 90% and 95% confidence intervals.

Figure A8 – Robustness: Excluding Donors



Notes: The bandwagon effect refers to the coefficient on the number of donors who decided to donate in the previous three days. The specification includes emergency-donor fixed effects. The strategic competition effect refers to the coefficient associated to the *ExpComp* coefficient, also relative to the previous three days, in a specification with emergency-donor and emergency-day fixed effects. The figure shows 90% and 95% confidence intervals.

Table A1 – List of Donors

Donor	No. of first commitments	Avg. duration (days)	Total contributed (USD million)
Argentina	22	24.4	.1
Australia	126	30.83	59.77
Austria	61	39.35	16.98
Belgium	74	41.67	37.43
Brazil	39	30.03	7.59
Canada	186	31.84	35.56
China	49	24.53	49.53
Cyprus	27	58.65	1.1
Czech Republic	67	30.72	6.95
Denmark	119	30.98	14.71
Estonia	33	19.76	1.96
Finland	60	39.24	21.42
France	144	28.34	51.32
Germany	266	38.7	53.96
Greece	50	25.03	6.94
Hungary	32	25.67	1.22
India	22	15.83	15.52
Indonesia	9	10.11	7.23
Ireland	113	36.64	23.74
Israel	26	16.68	2.83
Italy	152	31.37	39.35
Japan	201	21.7	79.93
Luxembourg	124	47.48	16.47
Mexico	18	40.5	5.44
Netherlands	100	31.06	50.42
New Zealand	84	36.58	31.8
Norway	173	41.62	47.37
Poland	34	29.04	9.03
Portugal	25	25.86	1.72
Russia	50	30.68	38.5
Saudi Arabia	67	39.28	408.69
Singapore	46	26.16	1.1
Slovak Republic	23	18.06	6.45
South Africa	15	33.5	1.81
South Korea	88	22.01	11.2
Spain	129	30.6	68.56
Sweden	208	37.71	40.02
Switzerland	138	49.67	32.01
Türkiye	74	37.71	24.13
United Arab Emirates	84	50.17	29.25
United Kingdom	133	33.85	75.01
United States	385	31	102.28
Venezuela	23	21.48	.12

Notes: The table lists all donor countries included in the analysis. For each donor, it reports the total number of (first) aid commitments made, the average duration, in days, between disaster start and the the first commitment, as well as the total amount, in million US dollars, contributed in these commitments. Data from EM-DAT (Guha-Sapir, 2024) and FTS (OCHA, 2024) for the period between 2000 and 2022.

Table A2 – Descriptive Statistics

	Mean	SD	Min	Max	Count
	Disaster-Level Analysis				
Duration (days)	33.51	36.39	1.00	180.00	3,081
Total deaths	9871.49	35432.37	1.00	222570.00	3,311
(R) UNSC	0.10	0.30	0.00	1.00	3,522
(R) UNGA Ideal Point	-0.46	0.61	-2.15	2.34	3,504
(R) GDP p.c. (log)	7.64	0.95	5.65	10.89	3,464
(R) Corruption Index	-0.56	0.62	-1.80	2.33	2,946
(R) Population (log)	16.94	2.03	9.30	21.01	3,513
(D) UNGA Ideal Point	1.05	0.82	-1.41	2.92	3,497
(D) GDP p.c. (log)	10.44	0.70	6.68	11.63	3,500
(D) Population (log)	17.08	1.64	12.97	21.05	3,522
Exports, D to R (log)	13.39	3.16	0.00	21.07	3,352
Imports, from R to D (log)	13.03	3.68	0.12	22.01	3,295
Δ UNGA	1.58	0.88	0.00	4.40	3,479
	Daily Analysis				
Aid	0.00	0.03	0.00	1.00	3,542,509
No. of donors (1d)	0.03	0.25	0.00	12.00	3,993,840
No. of donors	0.10	0.52	0.00	23.00	3,993,840
No. of donors (7d)	0.23	0.95	0.00	25.00	3,993,840
Export Competition	0.02	0.15	0.00	10.96	3,661,725
Export Competition (7d)	0.06	0.27	0.00	11.65	3,661,725
Import Competition	0.03	0.20	0.00	9.51	3,661,725
Import Competition (7d)	0.07	0.37	0.00	13.20	3,661,725
Geopolitical Alignment	0.07	0.39	0.00	19.55	3,975,080
Information	0.07	0.39	0.00	17.76	3,984,380
Aid Lead	0.01	0.09	0.00	1.00	851,400
ESI Lead	0.29	0.19	0.00	0.77	726,608
ISI Lead	0.30	0.25	0.00	0.99	726,608

Table A3 – G7 Donors

	Dependent Variable: *Aid*						
	CAN	FRA	DEU	ITA	JPN	GBR	USA
Aid	0.001	-0.003	-0.001	0.003	0.002	0.003**	0.000
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
ESI * Aid	0.012*	0.017*	0.013***	0.003	0.016***	-0.000	0.007**
	(0.007)	(0.010)	(0.004)	(0.008)	(0.006)	(0.006)	(0.003)
ISI * Aid	-0.003	0.012*	-0.001	0.003	-0.001	-0.005**	-0.000
	(0.002)	(0.006)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)
H(Daycount)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Emergency-Donor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Emergency-Day FE	No	No	No	No	No	No	No
N	3,092,243	3,111,236	3,137,368	3,110,705	3,098,166	3,119,227	3,147,169

Notes: Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Two-way clustered (at donor and recipient level) standard errors in parentheses. Baseline results using three-day window after decision day. G7 donors include Canada (CAN), France (FRA), Germany (DEU), Italy (ITA), Japan (JPN), the United Kingdom (GBR), and the United States (USA).

Table A4 – "Good" Donors

	Dependent Variable: *Aid*			
	DNK	NLD	NOR	SWE
Aid	-0.002	-0.002	0.001	0.002
	(0.003)	(0.002)	(0.002)	(0.001)
ESI * Aid	0.010	0.021*	0.007	0.002
	(0.006)	(0.012)	(0.010)	(0.006)
ISI * Aid	0.002	0.007	0.005	0.001
	(0.005)	(0.007)	(0.004)	(0.003)
H(Daycount)	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Emergency-Donor FE	Yes	Yes	Yes	Yes
Emergency-Day FE	No	No	No	No
N	3,053,653	3,096,628	2,922,518	3,052,840

Notes: Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Two-way clustered (at donor and recipient level) standard errors in parentheses. Baseline results using three-day window after decision day. "Good" donors include Denmark (DNK), the Netherlands (NLD), Norway (NOR), and Sweden (SWE).

Table A5 – Robustness: Adjusted Similarity Indices

	Dependent Variable: *Aid*			
	(1)	(2)	(3)	(4)
No. of donors	0.000		0.000	
	(0.000)		(0.000)	
Export Competition (Adj.)	0.490***	0.647***	0.260**	0.246**
	(0.140)	(0.124)	(0.116)	(0.101)
Import Competition (Adj.)	0.233***	0.268***	0.089*	0.113*
	(0.062)	(0.070)	(0.053)	(0.060)
H(Daycount)	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Emergency FE	Yes	Yes	Yes	Yes
Donor FE	Yes	Yes	Yes	Yes
Emergency-Donor FE	No	No	Yes	Yes
Emergency-Day FE	No	Yes	No	Yes
N	2,956,568	2,956,568	2,956,505	2,956,505

Notes: Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Two-way clustered (at donor and recipient level) standard errors in parentheses. Baseline results using three-day window after decision day. Coefficients and standard erros associated with $ExpComp^{Adj}$ and $ImpComp^{Adj}$ divided by thousand for presentation purposes.

Table A6 – Disaster Severity: Bandwagon

	Dependent Variable: *Aid*				
	(1)	(2)	(3)	(4)	(5)
No. of donors	0.000*	0.001*	0.001***	0.001***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Weekday FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Emergency-Donor FE	Yes	Yes	Yes	Yes	Yes
Emergency-Day FE	No	No	No	No	No
Quintile	Q1	Q2	Q3	Q4	Q5
N	683,887	648,198	634,942	620,488	517,409

Notes: Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Two-way clustered (at donor and recipient level) standard errors in parentheses. Baseline results using three-day window after decision day. The quintiles of disaster severity are calculated based on the death toll of each emergency.