The Speed of Emergency Aid

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Abstract

Timely assistance is a precondition for effective emergency relief in the aftermath of natural disasters. This article shows that donor countries react with more urgency to natural disasters in situations where they have stronger strategic interests. We analyze daily humanitarian aid decisions by 45 donor countries after 392 fast-onset natural disasters between 2000 and 2016 in a trilateral setting (i.e., lead donor, other donor, recipient). Our results show, first, that recipient-specific lead donors' aid decisions induce other donors to commit aid and, second, that commercial competition between donors is an important driver of the speed of aid. In particular, donors are more likely to commit aid in the days after the lead donor's decision if they have export structures more similar to the lead donor in the affected country.

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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 US$ 3 trillion (CRED & UNDRR, 2020). Although these events occur in both rich and poor countries at similar frequencies, they are often much more damaging in the developing world because of worse infrastructure and fewer capabilities to assist disaster victims (Kahn, 2005, Strömberg, 2007). Hence, many (developing) countries require international humanitarian assistance to cope with these catastrophes. Donor governments, usually from rich countries, then step in to provide emergency relief. This is important not only to deal with catastrophes' direct consequences, but also to help mitigating more long-term negative effects, ranging from a decline in life satisfaction and life expectancy to higher risk of conflicts erupting in the future (Neumayer and Plümper, 2007, Nel and Righarts, 2008, Luechinger and Raschky, 2009).[1] As climate change increases both the likelihood and the intensity of extreme weather events, the relevance of emergency aid will likely become even more salient in the future (IPCC, 2018).

When earthquakes strike or volcanoes erupt, a difference of a couple of days—if not hours—in the decision to provide aid can save hundreds of lives. As acknowledged by the international community, a fast provision of emergency relief in the aftermath of natural disasters is thus, in most cases, essential for its effectiveness. The 42 donors organized in the Good Humanitarian Donorship (GHD) initiative (most of which are included in our sample) endorse a common set of principles that call for rapid assistance. Explicit goals are to "strive to ensure flexible and timely funding" (Principle 5) and to "[m]aintain readiness to offer support to the implementation of humanitarian action" (Principle 17).[2] The commitment to provide quick disaster relief also figures prominently among the key priorities communicated by individual donors. The United States Agency for International Development (USAID), for example, declares that "[a]ll efforts must be made to ensure that timely and appropriate assistance is efficiently delivered to the neediest victims."[3] When needed, USAID's Office of U.S. Foreign Disaster Assistance (OFDA) claims to be able to send a Disaster Assistance Response Team (DART) "within hours of an emergency."[4] Given the importance of a fast response to disasters, it is crucial to evaluate aid activities not only based on their monetary volume, but also on response's timeliness.

The attention policymakers and aid practitioners devote to timely relief notwithstanding, this issue has not received sufficient scholarly consideration. In fact, to the best of our knowledge, our paper is the first to empirically analyze the speed of the (emergency) aid decision.[5] Despite donors' penchant for

[1] As Felbermayr and Gröschl (2014, p.96) note, "[d]isasters in developed countries destroy more physical capital but less human capital" compared to developing countries.

[2] The list of the 24 Principles and Good Practice of Humanitarian Donorship are available at `https://www.ghdinitiative.org/ghd/gns/principles-good-practice-of-ghd/principles-good-practice-ghd.html` (accessed November 2020).

[3] See the USAID's operational policy (chapter 251) at `https://www.usaid.gov/ads/policy/200/251` (accessed February 2021). Similarly, 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." For more information, see `https://www.irishaid.ie/media/irishaid/allwebsitemedia/20newsandpublications/publicationpdfsenglish/humanitarian-relief-policy1.pdf` (accessed November 2020).

[4] For more details, see `https://www.usaid.gov/sites/default/files/documents/1866/OFDA_Fact_Sheet_02-25-2019.pdf` (accessed March 2021).

[5] Previous work has investigated the speed of aid disbursements *after* the initial aid decision was made (Kilby, 2011, Kersting and Kilby, 2016). Moreover, our paper is related to McDowell (2017), who analyzes the speed of loan approval after countries have submitted a letter of intent to the International Monetary Fund. He finds that the approval speed increases with the financial exposure of the Fund's five major shareholders in the potential recipient country.

portraying humanitarian aid as strictly need-based, strategic (commercial and political) donor interests play a considerable role in allocation decisions (Drury et al., 2005, Fink and Redaelli, 2011, Raschky and Schwindt, 2012, Annen and Strickland, 2017). 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" (Clarke and Dercon, 2016, p.4). Therefore, we suspect that also the speed with which donors react to emergencies may not be driven solely by humanitarian concerns. Taking into consideration previous work on donor coordination or lack thereof (Aldasoro et al., 2010, Fuchs et al., 2015, Davies and Klasen, 2019), we posit that commercial and political competition between donors is a particularly important threat to a timely—and thus effective—aid provision.

We empirically investigate whether strategic interests—and donor competition in particular—accelerate the speed of donors' first emergency aid commitment in the aftermath of natural disasters. To do so, we combine daily data on aid flows from the UN Office for the Coordination of Humanitarian Affairs (OCHA, 2017) with disaster start dates provided by the International Disaster Database (Guha-Sapir, 2017). Our sample consists of 392 fast-onset natural disasters that took place in 121 (recipient) countries between 2000 and 2016, leading to almost 3,000 aid flows originating from 45 different donor countries.[6]

Considering how little we know about the speed of aid, we first analyze, descriptively, whether (donor and recipient) political and economic characteristics are associated with the speed with which countries decide to provide relief. If aid speed follows the same logic as aid allocation, we would expect that close trade partners and countries that are of higher geopolitical importance receive a more favorable treatment—i.e., faster assistance. Hence, we create a measure, in days, of the time that passes after the onset of an emergency before a donor commits (for the first time) to provide relief. In line with expectations, we find that donors react faster to natural disasters that occur in countries that are more important trade partners and more distant in terms of foreign-policy preferences—which is consistent with the argument that humanitarian assistance can be used as a cheaper, low-commitment tool to sway geopolitical foes (Fink and Redaelli, 2011).

In the main part of our analysis, we take full advantage of the fine-grained nature of our data by constructing a trilateral panel data set (i.e., lead donor, other donor, recipient) of humanitarian aid commitments at daily frequency. This data structure offers an ideal setting to analyze donors' strategic behavior. It allows us to identify how donors move after each other, and thus investigate whether their interaction has consequences for the speed of aid. That is, contrary to most other studies, which can only study the final allocation outcome, our approach comes thus with the advantage that we observe the process as it unfolds, day after day.

We first test, for each disaster event, if a donor is more likely to provide assistance after the lead donor committed to do so, and thus assess to what extent donors are subject to pressure from their peers (Round and Odedokun, 2004). Moreover, given widespread evidence of donors competing with each other (Mascarenhas and Sandler, 2006, Djankov et al., 2009, Davies and Klasen, 2019), we expect that the influence that a given lead donor has on the decision of other donors increases with the salience of their strategic interests. We capture these interests mainly in terms of competing commercial interests, and calculate the similarity in terms of export and import patterns between a pair of donors in a given recipient country (Finger and Kreinin, 1979, Fuchs et al., 2015). Our main hypothesis is that, when donors observe their competitors providing assistance to an important trade partner, 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.

[6]Our donor sample includes, in addition to G20 members, any country that has provided emergency aid at least once (on average) in each year in the period between 2000 and 2016.

To asses how recipient-year-specific leading donors steer the behavior of other aid providers, we do not impose *a priori* a fixed set of important donors that should be as relevant to all recipient countries. Instead, we follow Steinwand (2015)'s definition and empirically identify, for every year in each recipient country, who the lead donor is (if there is one at all). Broadly speaking, these are donors that typically maintain long-term bonds with the recipient countries under their sphere of influence, and make their leadership role evident to all other participants in the aid community. Therefore, we expect these donors to possess the greatest amount of local expertise, and to be thus in a position to dictate the pace to other donors. Since these are the natural first movers, they offer a good opportunity to identify chains of reaction, as one is able to distinguish who is moving after whom.

In our daily analysis, we are able to include, among others, emergency-day fixed effects, which absorb all disaster-specific daily variation that is common to all donors for a period of 180 days after disaster onset. This rules out the possibility that our results could be driven by confounding factors such as new information flows about these disasters that become available to the international community on a daily basis and likely influence the timing of aid commitments. Identification in this rigorous setting thus stems from within-day variation between donors.

The analysis of the daily interaction between donors shows, first, that lead donors indeed exert considerable influence over other donors' speed of reaction. The lead donor's decision to provide assistance increases by 7.6 percentage points the likelihood that another donor commits to aid in the next three days. In the context of emergency relief, this highlights that certain donors, given their leadership position, can serve as a powerful agent to accelerate aid provision and thus increase its overall effectiveness. Second, we find that the extent to which donors follow each other increases with their degree of commercial competition in a given recipient country. Donors are particularly sensitive to threats to their export interests. If a donor has a similar export structure to the lead donor in the affected country, it is more than 17 percentage points more likely to decide to provide aid after its competitor—i.e., the lead donor—has done so. This result is robust to the inclusion of other confounding channels, such as informational and geopolitical similarity, and—consistent with our interpretation of donors vying to curry favors with recipient countries—driven by government-to-government (rather than to IOs or NGOs) and financial (rather than in-kind) aid. That is, the types of aid that give the recipient the most freedom to decide how to use the funds and are thus likely to be preferred (Raschky and Schwindt, 2012).

Taken together, our results show that donor countries react with more urgency to natural disasters in situations where they have stronger commercial interests at stake. Decisions to assist are also affected to some degree by geopolitical considerations. Our findings thus 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). Hence, this study raises important concerns about the neutrality of bilateral humanitarian aid provision and about its effectiveness in general, thus underscoring the necessity to promote mechanisms that foster donor cooperation and coordinated humanitarian assistance in international fora.

We proceed as follows: Section 2 describes the data and provides a descriptive analysis of what explains the variation in the speed of the aid at the emergency-event level. In Section 3, we present our main analysis based on daily (i.e., event-day) aid decisions. Finally, Section 4 summarizes our paper and concludes.

2 Measuring the Speed of Aid

In this section, we introduce the data and a measure of aid speed, namely the *duration* (in days) between disaster start and donors' first commitment to assist, which we then use to analyze the factors that are associated with the speed of emergency aid at the disaster-event level. Specifically, we examine whether the promptness with which donors react to catastrophes is associated with disaster severity, need indicators, and variables that capture donors' commercial and political interests.

2.1 Data

Our measure of the speed of aid relies on data on humanitarian aid commitments from the Financial Tracking System (FTS) of the UN Office for the Coordination of Humanitarian Affairs (OCHA, 2017). Humanitarian assistance is defined as "[a]n intervention to help people affected by natural disasters and conflict to meet their basic needs and rights" (OCHA, 2017). The FTS tracks humanitarian funding flows worldwide and is based on self-reported information, provided by either donor governments, recipient agencies, collected from donor websites, or quoted in pledging conferences.[7] 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 encompasses a wide range of donor countries.[8] It is crucial for our purposes that the database covers humanitarian assistance in response to natural disasters and contains information on individual decision dates.

While the database covers information on aid flows provided by 166 bilateral donors, including countries such as the Democratic Republic of Congo and North Korea, we focus on those with significant donor activities. As such, we limit our analysis to the behavior of the G20 members and all other countries that have provided emergency aid to at least one disaster event per year, on average. In other words, we remove countries that do not satisfy the threshold of 17 records of emergency aid provision in the 17-year period (2000 to 2016) included in the sample. Thus, we are left with 45 donor countries, which provided more than 2,800 emergency aid flows to 121 (recipient) countries.[9] 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, 2017).[10]

We then measure donor country i's speed of aid after disaster event k in recipient country r by computing the duration, in days, from disaster onset, $StartDate_{i,k,r,t}$,[11] until the day on which donor

[7]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, refer to `https://fts.unocha.org/sites/default/files/criteria_for_inclusion_2017.pdf` (accessed April 2020). 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.

[8]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.

[9]Table 8 in the Appendix reports all donor countries in our sample together with the number of aid provisions, amount contributed, and average duration.

[10]Committed and contributed funds, on the other hand, constitute either a *de facto* payment, guaranteed by a signed contract, or the actual transfer of funds and in-kind goods from the donor to the recipient.

[11]$StartDate_{i,k,r,t}$ denotes the start date of the disaster event k as registered on the International Disaster Database (Guha-Sapir, 2017), maintained by the Centre for Research on the Epidemiology of Disasters (CRED). 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—information on 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,

i first decided to provide assistance to recipient r to cope with disaster event k, $DecisionDate_{i,k,r,t}$.[12] Formally, we define:

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

where a value of 1 indicates that the decision is taken on the start day of the disaster event and higher values imply slower aid speed.[13] In the regression models in this section, we use the logarithm of this measure as the dependent variable.

From the resulting difference, we exclude aid flows with a decision time greater than or equal to 180 days, since aid delivered with such a delay hardly aims at urgent needs that require speedy assistance. The selection of 180 days as cut-off level is in line with the UN's definition of a flash appeal, which structures a coordinated humanitarian response for up to six months after the start of an emergency.[14]

To be able to precisely measure the aid speed, we restrict our analysis to disaster types with a clearly identifiable start date. This means that we, similarly to Fink and Redaelli (2011), restrict our analysis to fast-onset disasters, and thus exclude events such as drought, extreme temperature, and insect infestation. The remaining disaster types include earthquakes, floods, landslides, storms, and volcanic activity. In a second step, we keep only those events that have a precise start day, i.e., exclude entries for which only a start month or year is available. This focus on fast-onset disasters comes with the advantage that it mitigates endogeneity concerns, since the exact outburst timing of these fast-onset disasters is largely unpredictable.[15] 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 392 fast-onset disasters. Since 29 of these affect more than one country at the same time, we end up with 450 disaster events, i.e., disaster-recipient pairs.[16] Table 1 reports disaster-type-specific information on the frequency and severity of disasters, as well as on the average number of donors active per catastrophe in our sample.

Figure 1 illustrates how the distribution of our speed measure varies according to different dimensions. The upper-left panel shows significant heterogeneity with respect to disaster type. Donor countries' response time is the shortest after earthquakes, followed by storms. Landslides trigger the slowest response. Turning to differences among four of the most active donor countries, Japan has the shortest average response time to natural disasters, followed by the United States. Germany and Norway are

(iii) a state of emergency has been declared, or (iv) a call for international assistance has been made in response to the wreck.

[12] FTS defines the variable *decision date* as the "[d]ate on which a donor is reported to have made a funding commitment" (see FTS website at `https://fts.unocha.org/glossary`; accessed September 2020). Rather than studying the decision day, one may want to analyze information on the exact day on which aid packages reach the disaster area, or when funds are transferred. Unfortunately, this information is not available for most project records. However, these dates may be more appropriate to study aid effectiveness rather than—as we do—the political decision to provide aid.

[13] 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.

[14] More information at `https://www.unocha.org/sites/dms/CAP/FAs_What_you_need_to_know.pdf` (accessed April 2020).

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

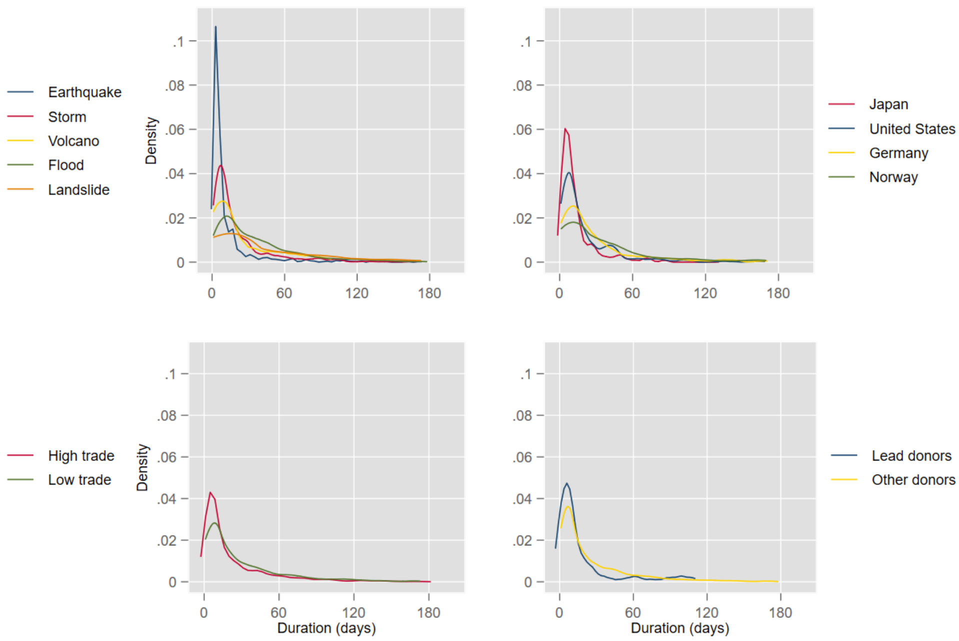
[16] We define a disaster event as a disaster in a specific country. For example, we treat the 2004 Indian Ocean tsunami as nine disaster events as it affected nine countries in our sample: India, Indonesia, Malaysia, Maldives, Myanmar, Seychelles, Somalia, Sri Lanka, and Thailand.

Table 1 – Fast-onset Natural Disasters (2000–2016)

	No. of events	Avg. no. people killed	Avg. no. people affected	Avg. no. donors
Earthquake	72	31,088	3,251,377	23
Flood	228	188	2,985,759	11
Landslide	16	472	65,084	10
Storm	118	8,180	1,945,625	15
Volcanic activity	16	65	70,875	13
Total	450	10,691	2,661,198	15

significantly slower. In the bottom-left corner, dividing the sample according to high and low trade ties between donor and disaster-affected country, we find that countries with closer commercial links (i.e., donor-recipient pairs with above-median export and import flows) get faster relief. Finally, the bottom-right panel shows that recipient-year-specific lead donors provide assistance significantly faster than their peers, a feature that we exploit and discuss in more detail in Section 3. Overall, we conclude from this figure that the speed of aid shows considerable variation across disaster types, donor countries, and also according to the strength of commercial ties between donor and recipient.[17]

Figure 1 – Duration Distribution



2.2 Correlates of the Speed of Aid

In the context of humanitarian aid, whose ethical foundations were established in humanitarian law, it would be particularly concerning if the promptness of donor reaction were to be driven by ulterior motivations. In contrast to the more general development assistance, emergency relief's sole purpose is to temporarily assist individuals in times of great vulnerability, with no strings attached, and should be thus "provided in accordance with the principles of humanity, neutrality and impartiality" (OCHA,

[17]Figure 4, in the Appendix, shows nevertheless no clear trend in average and median duration across disasters over time.

2009). To analyze whether this is indeed the case, we regress our measure of speed of emergency aid, $Duration$, on selected indicators of (bilateral) commercial and geopolitical motivations using ordinary least squares.[18]

First, we investigate whether close trade partners receive preferential treatment, as speedier assistance may help mitigate the damage to commercial ties (Gassebner et al., 2010). If a donor country exports a substantial part of its production to a country that has been 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. We measure trade ties with (the logarithm of) both exports and imports flows between donor and recipient in constant 2010 US dollars (IMF, 2017).

Second, we examine the role of geopolitical ties for the speed of aid. It is not clear, *a priori*, how political alignment may affect the speed of humanitarian assistance. On the one hand, closer political ties could be associated with countries receiving faster aid from their allies. Donors may speed up their emergency aid to express their support for befriended countries or even to ensure the survival of politically-aligned governments in cases where a severe disaster threatens the political stability of an entire country (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. This second channel seems to be more likely to influence emergency aid contributions rather than general development assistance. In contrast to emergency aid, 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). Many aid initiatives have long-run goals, such as the alleviation of poverty, which require certain stability in bilateral relations. 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 in more flexible and low-commitment arrangements.

The case of the 2010 Haiti earthquake provides a prime example of these two opposing mechanisms. In the aftermath of the disaster, Taiwan—which currently maintains diplomatic relations with 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 as 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. In a similar manner, we expect that less affine countries receive speedier assistance.

To measure political ties, we include the voting alignment at the UN General Assembly between donor and recipient, which is a widely used indicator in the empirical aid literature (e.g., Thacker, 1999, Kilby, 2009, 2011, Faye and Niehaus, 2012). 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.

[18] In the Appendix (Tables 6 and 7), we also present results for unilateral (recipient and donor) characteristics.

(2017).[19] That is, $UNGA\Delta_{i,r,t} = |idealpoint_{i,t} - idealpoint_{r,t}|$.[20]

Additionally, to account for transportation costs of aid provided in kind and for cultural similarities between countries, we control for (the logarithm of) geographic distance in kilometers between donor i and recipient r,[21] and for a binary variable that takes a value of one if both countries share an official language.[22]

Table 2 presents the results for increasingly conservative sets of fixed effects to deal with unobserved confounding characteristics. We start with emergency fixed effects in columns 1 and 2, add donor-year fixed effects in columns 3 and 4, include donor-disaster-type fixed effects in columns 5 and 6, and donor-recipient fixed effects in columns 7 and 8.[23] We show results for the full sample (odd columns) and for G20 donors only (even columns). This allows us to focus on (mostly) large aid providers that presumably care the most about consolidating their own agendas abroad and have more agency to tie the speed of aid provision to their objectives. We observe the following. First, there is evidence that commercial and geopolitical ties are associated with relief promptness. We find that, in most specifications, the more a donor country relies on imports from the recipient country, the faster, on average, it provides assistance. According to column 8, our preferred specification, doubling the imported amount decreases *Duration* by 10%. In this strict model, which includes also donor-recipient fixed effects, for the restricted sample of G20 donors (column 8), our results indicate that recipients that are less politically aligned with donors receive aid significantly quicker. This is in line with the broader literature on humanitarian aid allocation, and in particular with Fink and Redaelli (2011) and Annen and Strickland (2017), who argue that emergency aid, due to its more short-term horizon, is frequently used as a less costly tool (in comparison to official development aid) to try to sway political "foes."[24] In our settings, however, due to our fixed-effect structure, these findings imply in particular that, for a given donor-recipient pair, aid provision gets faster (slower) if the pair become politically more distant (closer) over time.

Table 6 (in the Appendix) provides additional evidence of distortions in the speed of emergency aid. In the strictest specifications, we find that more democratic countries and recipients that occupy a seat at the UN Security Council at the time of the disaster receive, on average, faster assistance.[25] We report that donors are nevertheless responsive to need, as aid speed increases significantly with the number of disaster victims.

Taken together, these results suggest in particular that commercial and geopolitical ties affect the speed with which donors respond to humanitarian crises. Nevertheless, despite controlling for many confounding factors and including various fixed effects, these findings are mostly descriptive. What is

[19] For each year, Bailey et al. (2017) estimate a country's ideal point within a one-dimensional preference space. How a country votes (i.e., yay, nay or abstain) in each UNGA vote is thus seen as a function of its ideal point. Therefore, the more similar are the voting behaviors of two countries, the closer their ideal points are, and hence the smaller the absolute difference between the two.

[20] Table 9 in the Appendix provides descriptive statistics of all variables.

[21] We define the distance between countries as the distance between the major cities of the two countries, weighted by their population size. See Mayer and Zignago (2011).

[22] Past research has shown that shorter distance and same language can facilitate the provision of emergency aid (e.g., Strömberg, 2007). We have also experimented controlling for donor and recipient having common colonial history and common major religion, but, contrary to sharing a language, these similarities did not turn out to play a significant role (results not shown).

[23] We include disaster-type dummies to account for unobserved characteristics of the different disaster types. It is conceivable that different types of disasters *per se* trigger different responses from the aid community. For example, Eisensee and Strömberg (2007) report that the newsworthiness of emergencies depends on disaster type.

[24] Bommer et al. (2019) show that humanitarian aid can also be distorted by regional differences within recipient countries, and favor, for instance, the birth region of political leaders.

[25] See Kuziemko and Werker (2006), Dreher et al. (2009*a*) and Vreeland and Dreher (2014) for a discussion on why UN Security Council members would receive more aid.

more, our estimation sample only includes information on the decision time if the respective donor has committed aid after a specific disaster, and we thus face the problem of incidental truncation of our data. To mitigate these concerns, we switch next to a daily analysis.

Table 2 – Correlates of the Speed of Aid

	Dependent Variable: *Duration (log)*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exports, D to R (log)	-0.0492***	-0.0278	-0.0158	0.0086	-0.0120	0.0158	-0.0312	-0.1485
	(0.0144)	(0.0201)	(0.0161)	(0.0220)	(0.0171)	(0.0218)	(0.0674)	(0.1818)
Imports, from R to D (log)	-0.0297**	-0.0715***	-0.0313**	-0.0512***	-0.0307**	-0.0508***	-0.0595	-0.1452*
	(0.0136)	(0.0198)	(0.0147)	(0.0152)	(0.0130)	(0.0158)	(0.0629)	(0.0693)
UNGA delta	-0.1823***	-0.1389**	0.0707	-0.1026	0.0355	-0.1638*	-0.9570	-2.0106**
	(0.0535)	(0.0630)	(0.1504)	(0.0866)	(0.1505)	(0.0836)	(1.4077)	(0.7250)
Distance (log)	0.0429	0.0121	0.1687**	0.1574**	0.1715**	0.1563*		
	(0.0694)	(0.0899)	(0.0775)	(0.0738)	(0.0845)	(0.0753)		
Common language	-0.1090	-0.0749	-0.1903**	-0.1545	-0.1682*	-0.1212		
	(0.0921)	(0.0845)	(0.0811)	(0.0925)	(0.0943)	(0.0982)		
Emergency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Donor-Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Donor-Disaster FE	No	No	No	No	Yes	Yes	Yes	Yes
Donor-Recipient FE	No	No	No	No	No	No	Yes	Yes
Only G20 Donors	No	Yes	No	Yes	No	Yes	No	Yes
N	2582	1299	2427	1246	2390	1224	1369	777

Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Two-way clustered (at donor and recipient level) standard errors in parentheses. Dependent variable: *Duration*.

3 Daily Analysis

To dive deeper into the speed of emergency aid and donor decision-making, we turn our analysis to the event-day level and focus on reaction chains sparked by lead donors. These aid providers, usually faster than their peers (Figure 1), offer a good opportunity for identifying the logic behind donor interaction. Thus, for each disaster event (that has a lead donor), we study how the behavior of these recipient-year-specific leaders affects the course of action of other donors. In particular, we examine to what extent lead donors' aid decisions accelerate the reaction of their peers, and whether strategic (commercial and geopolitical) competition strengthens this effect.[26]

By, roughly speaking, watching the response to disaster emergencies as it unfolds, day after day, we thus improve over existing studies of humanitarian assistance by being able to identify novel patterns of interaction and competition among donors, as well as important features of the political economy of humanitarian aid that have been neglected so far. Instead of only looking at the final picture, as the previous literature does, our unique vantage point lets us track the implications that the decision of one donor has for other aid providers. Thus, in addition to observing who is moving after whom, we can single out strategic drivers of daily aid decisions.

More precisely, we test two hypotheses. First, we know that that aid decisions are often influenced by bandwagon effects and peer pressure from other donors (Round and Odedokun, 2004, Fink and Redaelli, 2011, e.g.,). So far, however, we have only been able to observe this herding behavior in the final allocation, and cannot say whether donors happen to be making, autonomously, similar decisions

[26]Donors acting according to their own interests, and thus failing to coordinate, is an important (if not the most important) obstacle to improving aid effectiveness (e.g., Mascarenhas and Sandler, 2006, Bourguignon and Platteau, 2015).

or are rather responding to a common trigger. We thus hypothesize that the lead donor's decision to aid works as a powerful catalyst to trigger the behavior of other donors (bandwagon hypothesis). The reason is that donors observe what their peers are doing and frequently communicate with one another (informally or formally via international organizations) about their decisions and in this process end up taking cues from important players that have more in-loco expertise. In the context of emergency aid, if indeed capable of prompting other donors to donate faster, lead donors can act as a powerful force to improve aid effectiveness and reduce the suffering in the aftermath of natural disasters.[27]

Second, there is abundant evidence that donors allocate (humanitarian) aid based not only on recipients' needs, but also on their own strategic interests (Drury et al., 2005, Fink and Redaelli, 2011, e.g.,), and that donors compete with each other in order to secure their own agendas (Djankov et al., 2009, Davies and Klasen, 2019). Moreover, in Section 2 above, we provide descriptive evidence that also the speed with which donors react to emergencies is distorted by their own interests. Therefore, we conjecture that lead donors influence their peers not only via a bandwagon effect, but rather that this reaction is reinforced by the strategic interests of these other donors. More precisely, the more the interests of a particular donor collide with the lead donor's, the faster we expect the former to react to the decision of the latter (competition hypothesis). That is, on top of a bandwagon effect that is presumably common to all players in the aid community, if a pair of donors vie for the goodwill of the recipient country, one is even more likely to engage and try to secure its interests if its rival has already done so, such that the net effect that the lead donor has on other donors varies according to their degree of competition. Below, we devote most of our attention to discuss two particular sources of (commercial) competition between donors: exports and imports interests.

3.1 Empirical Strategy

To test our two 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-disaster event by day. That is, for every disaster event, we observe each of our 45 donor countries for a maximum of 180 days from disaster start until the day in which the donor (first) decides to provide aid.[28] We thus analyze whether and how, during a specific emergency, the decision of lead donors to provide aid today influences the behavior of other (potential) donors in the next three days and, by doing so, nudges the latter to speed up.[29]

Next, we proceed the concept of lead donors. To begin with, according to Steinwand (2015), two attributes separate lead donorship from conventional aid provision. First, lead donors typically maintain long-term bonds with the recipient countries under their sphere of influence, and their leadership role is evident to all participants in the aid community. Second, and particularly relevant in our case, lead donors are in a privileged position to steer the behavior of other donors. 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 (2020)[30] and follow Steinwand (2015) by requiring

[27] *A priori*, the aid decision of lead donors can either encourage other donors to provide aid or, alternatively, crowd out resources that would otherwise have been donated. In the former case, competition between donors could induce donors to help where the competitor has aided (Fuchs et al., 2015). Peer pressure could equally lead to more aid (Mosley, 1985). In the latter case, donors could reduce their aid effort if aid is understood as an international public good (Schweinberger and Lahiri, 2006).

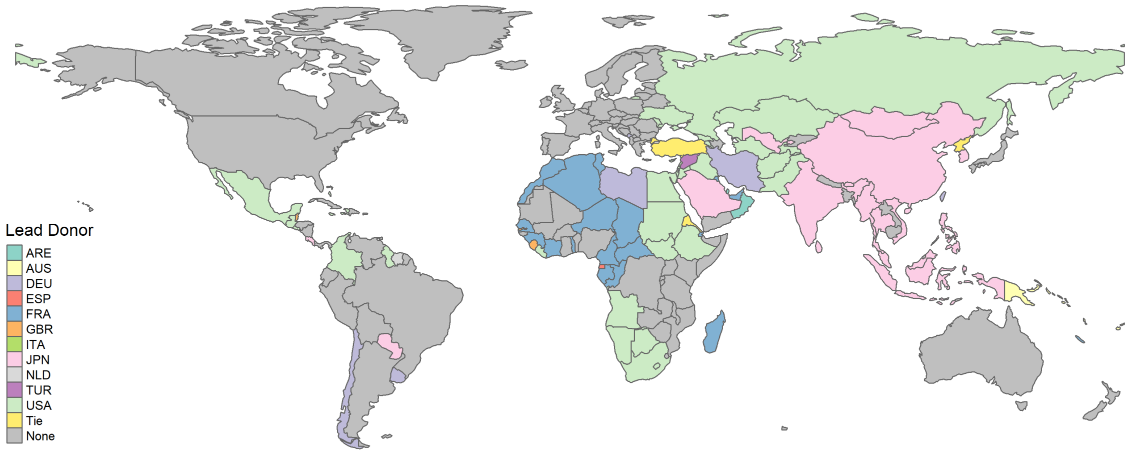
[28] In most specifications in this section, some donors inevitably leave the sample, either because they never provided assistance in response to a disaster in which the major donor has also been involved or due to the fixed-effect structure.

[29] As shown in Table 4 and Figure 3, our results are robust to the selection of different time windows.

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

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;[31] (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;[32] and (v) the lead donor must operate in a concentrated environment (i.e., the recipient country has a low donor fragmentation).[33] 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 24% 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 sample period.

Figure 2 – Most Frequent Lead Donor by Country (2000–2016)



Most frequent lead donor (between 2000 and 2016) across different recipient countries according to definition in Steinwand (2015). Data on total (gross) ODA disbursement from OECD (2020). New Zealand and Portugal are the most frequent lead donors in some small island states that do not show up in the map.

To investigate the role of commercial interests in our event-day setting, we construct trilateral indicators of export and import similarity between donors i and j with respect to the recipient country r based on sectoral (SITC, Rev. 2) international trade data (Growth Lab, 2019) and, following Finger and Kreinin (1979), calculate both export and import similarity indices (ESI and ISI, respectively) for each donor pair in a particular recipient country.[34] Specifically, the Export Similarity Index ESI of donor countries i and j in recipient country r and year t is given by:

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

where $X_s^{i,r,k,t}$ represents i's exports in sector s to r in year t as a share of i's total exports to r in t. Analogously, we use the sectoral import share to calculate the Import Similarity Index ISI. The indices

[31] 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.

[32] 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.

[33] 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.

[34] See Fuchs et al. (2015) and Asmus et al. (2021) for applications of the export and import similarity indices in the aid literature.

take values between zero and one, with one indicating perfect similarity.[35] In both cases, the higher the overlap between a pair of donors in a given recipient, arguably the higher their degree of competition with one another.

With this in mind, we proceed to estimate the following regression equation using ordinary least squares:

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

where our dependent variable, $Aid_{i,k,r,d}$, is 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.[36] On the right-hand side of the equation, we include a binary variable, $Aid_{j,k,r,[d-3,d-1]}$, that indicates whether the recipient's lead donor j has decided to provide aid within the last three days, $[d-3, d-1]$.[37] We further add the two similarity indices introduced above, $ESI_{i,j,k,r,t-1}$ and $ISI_{i,j,k,r,t-1}$, and their interactions with $Aid_{j,k,r,d-1}$.[38] In terms of the discussion above, the bandwagon hypothesis implies positive γ_1 and the competition hypothesis requires positive γ_2.

Moreover, 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 onset on the decision to provide assistance.[39] To account for unobserved characteristics that may influence the timing of aid provision, we include in all specifications weekday, day-of-the-month, month, donor and emergency fixed effects. We are thus able to remove, for instance, all the time-invariant (during a particular emergency) donor and recipient characteristics that influence the speed of assistance, such as donor aid infrastructure and particularities of each type of disaster, but are unrelated to the influence of lead donors.

In our preferred specification, we also add emergency-day fixed effects, i.e., 179 binary variables for each day after the start of each emergency. Although this comes with the disadvantage of no longer being able to estimate γ_1, i.e., the baseline effect that the lead donor decision to provide aid has on the behavior of other donors, it significantly improves the identification of the interaction term and, in turn, our ability to test the competition hypothesis. Once we control for all emergency-day-specific variation that is common to all donors (e.g., new information on a given disaster becoming available to the international aid community), we are able to pin down in which ways a donor's decision (not) to follow the lead donor depends on its strategic (trilateral) interests.

[35] Figure 5 in the Appendix shows the average ESI and ISI between the United States and Japan, two important donor countries in our sample, for each recipient country.

[36] Note that we focus on the binary decision to provide aid (and not on the amount provided) as this is arguably the decision in which donors' strategic considerations are the most dominant (Drury et al., 2005).

[37] We use a three-day period rather than a simple one-day lag 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 to alternative window lengths below.

[38] The similarity indices do not vary daily, but rather yearly, which is why they are indexed by t not d. We lag these annual indices by one year.

[39] In our baseline specification, we control for a polynomial function of degree 3. Moreover, this polynomial is redundant when emergency-day fixed effects are included.

3.2 Main Results

Table 3 presents the main results for the event-day-level analysis. We examine whether donors react to the aid decision of recipient-year-specific lead donors (column 1) and whether this reaction is a function of donors' export similarity (columns 2 and 3), import similarity (columns 4 and 5), or both (columns 6 and 7). We find that a commitment to provide emergency aid by the lead donor significantly increases the probability that other donors will also decide to commit aid during the following three days. All else being equal, the likelihood that a donor provides aid increases by 7.6 percentage points (column 1). This effect is sizable in light of the average probability to aid of 4 percent and is in line with the bandwagon hypothesis.

Table 3 – Lead Donors and Commercial Competition: Main Results

	Dependent Variable: *Aid*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Aid Lead	0.076***	0.041***		0.061**		0.040**	
	(0.014)	(0.012)		(0.024)		(0.020)	
ESI Lead		0.051**	0.059***			0.049**	0.058**
		(0.022)	(0.020)			(0.023)	(0.022)
ESI * Aid Lead		0.113***	0.172***			0.107***	0.202***
		(0.039)	(0.048)			(0.040)	(0.056)
ISI Lead				0.012	0.008	0.005	-0.000
				(0.023)	(0.019)	(0.020)	(0.016)
ISI * Aid Lead				0.044	-0.019	0.010	-0.067
				(0.080)	(0.073)	(0.080)	(0.063)
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	No	Yes
N	14755	14755	11663	14755	11663	14755	11663

Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Two-way clustered (at donor and recipient level) standard errors in parentheses. All regressions include weekday, day of the month, month, donor and emergency fixed effects, and a 3rd-order polynomial function of the number of days passed between disaster start and each donor's decision to provide first assistance. Baseline results using 3-day window after decision day.

Turning to the role of commercial interests, we observe that the likelihood that donors follow the lead donor increases with their export similarity in the recipient country (column 2). The interaction effect with *ESI* is positive as expected and statistically significant at the 1% level. This also holds when we include emergency-day fixed effects in column 3, i.e., control for all variation on disaster impact that is common on a specific day. In quantitative terms, the lead donor commitment makes it 17.2 percentage points more likely that a donor country with an identical export structure (in a given affected country) also decides to provide aid within the next three days. Applying the average *ESI* in our sample (0.07), we observe that the average donor is 1.2 percentage points more likely to provide aid. In sum, these results show that lead donors induce other donors to speed up their aid giving and that this effect is more pronounced if the respective donors compete over export markets. These results confirm one of the main findings from Section 2 in this more rigorous setting: commercial interests bias the speed of aid in emergency situations, which corroborates the competition hypothesis.

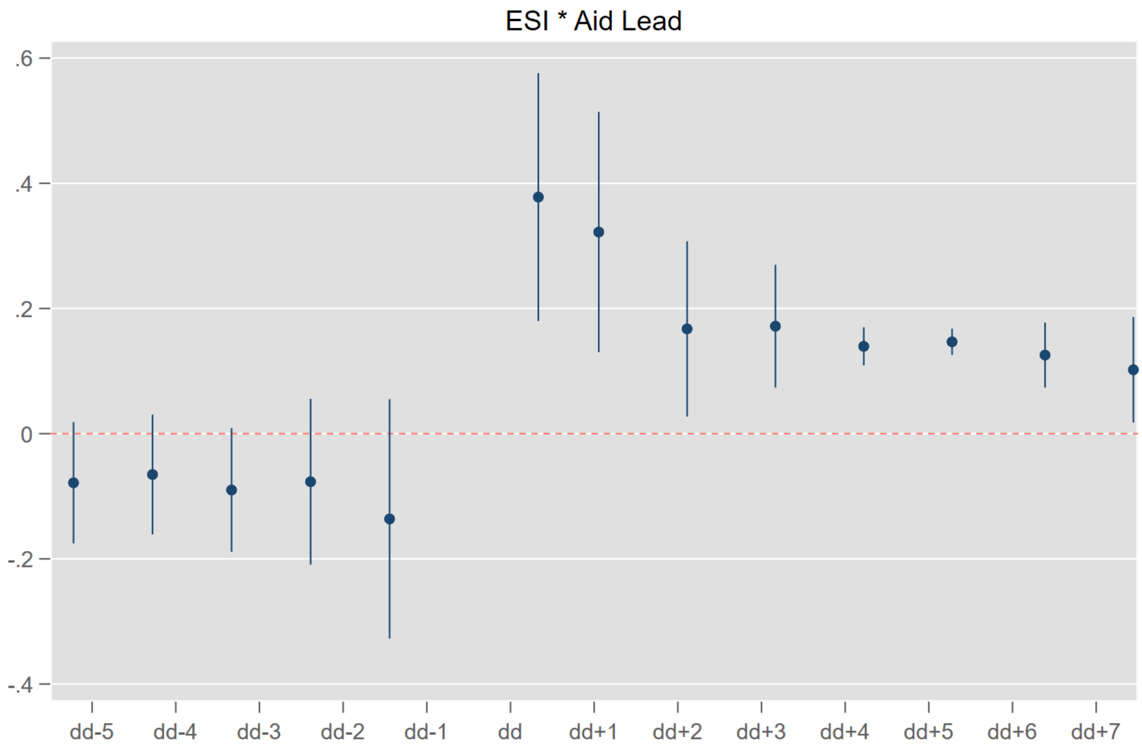
By contrast, we find no such effects for import similarity, and thus competition over import goods does not appear to lead to a similar crowding-in effect (columns 4 and 5). The level effect of the lead-donor commitment remains positive and statistically significant, but the interaction term with ISI does not reach statistical significance at conventional levels.

3.3 Extensions and Robustness Checks

In columns 1 to 7 of Table 4, we run several additional regressions to test the robustness of our results, and we use as baseline our preferred (and strictest) specification with emergency-day fixed effects from above. In column 1, to control for (unobserved) characteristics that are specific to a donor in a concrete disaster episode, we replace donor and emergency fixed effects with fixed effects for each pair of donor and disaster event. In this stricter specification, our coefficient of interest continues to be positive (as well as similar in magnitude) and significant at the 1% level.

Second, the choice of a three-day response window might appear arbitrary. In column 2 of Table 4, we thus replace the three-day window by a one-week window. Our finding is robust to this alteration. The effect becomes somewhat smaller and remains significant only at the 5%-level. This is hardly surprising, as the influence of the lead donor likely dissipates over time. We repeat the exercise with decision-day windows of one to seven days in Figure 3. Again, our findings are similar but weaker with longer windows as one would expect. The same figure also contains a "placebo test" where we look at one to five days *before* the lead donors has decided to help. 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 being followed by other donors—and not the other way around.[40]

Figure 3 – Lead Donors and Commercial Competition: Various Reaction Windows



Notes: The figure shows the coefficient for ESI * Aid Lead with different time windows, together with 95% confidence intervals. Regressions include weekday, day-of-the-month, month, donor, emergency, and emergency-day fixed effects.

[40]Figure 6, in the Appendix, shows a similar exercise for the aid coefficient.

Table 4 – Lead Donors and Commercial Competition: Robustness

	Dependent Variable: *Aid*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ESI * Aid Lead	0.170***		0.161**	0.153***	0.173***		
	(0.043)		(0.068)	(0.046)	(0.048)		
ESI Lead		0.058***	0.061**	0.060***	0.051**		
		(0.021)	(0.029)	(0.020)	(0.019)		
ESI * Aid Lead (7d)		0.102**					
		(0.041)					
InfoSI Lead			-0.060				
			(0.043)				
InfoSI * Aid Lead			0.036				
			(0.058)				
PSI Lead				-0.013			
				(0.059)			
PSI * Aid Lead				0.133*			
				(0.066)			
KeyISI Lead					0.030***		
					(0.008)		
KeyISI * Aid Lead					-0.010		
					(0.040)		
ESI USA						0.043***	
						(0.008)	
ESI * Aid USA						0.102*	
						(0.058)	
ESI SWE							0.025**
							(0.011)
ESI * Aid SWE							0.027
							(0.053)
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	No	Yes	Yes	Yes	Yes	Yes	Yes
Donor FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Emergency-Donor FE	Yes	No	No	No	No	No	No
Emergency-Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11638	11663	8878	11578	11663	61760	61760

Notes: Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Two-way clustered (at donor and recipient level) standard errors in parentheses. All regressions include weekday, day of the month, month, donor and emergency fixed effects, and a 3rd-order polynomial function of the number of days passed between disaster start and each donor's decision to provide first assistance. Baseline results using 3-day window after decision day.

Third, one might be concerned that our measures of commercial similarity are actually picking up dimensions of similarity other than export similarity and thus just proxying for the underlying (unobserved) affinity between donors. We examine two alternative explanations: information and political alignment. Starting with information, it is possible that not all donors receive information about disaster impact at the same time. Thus, one could expect that more similar donors receive these news at more similar frequencies. If export similarity happens to be correlated with information transmission between countries, our results above for ESI could be driven by this spurious correlation.[41]

[41] The fact that we did not find similar results for ISI is nevertheless reassuring in this sense. If our similarity indices were just capturing some underlying affinity between donors, it would likely affect ISI

To account for this unlikely but possible bias, we construct an information similarity index ($InfoSI$) based on the difference in informational globalization levels between donor i and lead donor j: $KOFI\Delta_{i,j,t} = |KOFI_{i,t} - KOFI_{j,t}|$, where $KOFI$ is the informational component of the KOF globalization index (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. To obtain $InfoSI$, we normalize $KOFI\Delta_{i,j,t}$ as follows:

$$InfoSI_{i,j,t} = \frac{-KOFI\Delta_{i,j,t} - Min(-KOFI\Delta_{i,j,t})}{Max(-KOFI\Delta_{i,j,t}) - Min(-KOFI\Delta_{i,j,t})} \in [0,1] \tag{4}$$

We expect that a pair of countries with a high $InfoSI$ obtain new information about a given disaster at more similar times, and thus include it (interacted with *Aid*) as an additional explanatory variable in equation 3.1.[42] If the informational channel was spuriously driving our results, the interacted $InfoSI$ coefficient should dominate and render the interacted ESI coefficient insignificant.

Based on the results presented in column 3 of Table 4, the effect of export similarity remains very similar, whereas the interacted $InfoSI$ coefficient does not reach statistical significance at conventional levels. This provides additional evidence 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 competitors in a given recipient country.

Fourth, another potential confounder is geopolitical alignment. Although we judge it unlikely, it could be that countries with a similar export structure are more politically aligned and we thus falsely attribute our result to commercial competition rather than geopolitical motivations. To rule out this possibility, we draw from a vast literature that uses voting alignment at the United Nations General Assembly to create a political similarity index, which we call PSI (e.g., Thacker, 1999, Kilby, 2009, Dreher et al., 2008). It measures geopolitical affinity between donor countries based on countries' voting behavior. We follow our approach in Section 2, but now use the ideal-point distance between donors, i.e., $UNGA\Delta_{i,j,t} = |idealpoint_{i,t} - idealpoint_{j,t}|$ (data from Bailey et al. 2017). Then, we construct an index that increases with the similarity of votes cast by donor countries i and j in year t:

$$PSI_{i,j,t} = \frac{-UNGA\Delta_{i,j,t} - Min(-UNGA\Delta_{i,j,t})}{Max(-UNGA\Delta_{i,j,t}) - Min(-UNGA\Delta_{i,j,t})} \in [0,1] \tag{5}$$

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 coefficient for the interacted PSI 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 from column 4 of Table 4, donor countries that are politically aligned with the lead donor are more likely to follow it when it has provided aid to an emergency within the last three days. The respective coefficient is positive and statistically significant at the 10%-level. Rather than political competition, our results indicate that the crowding-in effect of lead donors increases with foreign-policy alignment, which could thus signal policy coordination and/or international leadership. Most importantly, however, our main finding of export competition speeding up emergency aid remains largely unaltered.

Fifth, column 5 re-investigates our non-finding with respect to import similarity. It might be that only competition over strategic import goods, such as scarce natural resources, matters for commercial

as well.

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

competition in humanitarian assistance. This is why we re-run our regressions with an import similarity index for key and strategic goods ($KeyISI$) rather than the overall ISI. Specifically, we include metalliferous ores and metal scrap (SITC2 28), all fuel subcategories (32, 33, 34, 35), medicinal and pharmaceutical products (54), and iron and steel (67).[43] Again, import similarity of strategic goods does not matter, which is in line with our earlier result for overall imports. It is commercial competition over export markets that speeds up emergency aid decisions.

Sixth, given that the United States is the largest and most important (lead) donor in our sample, we test in column 6 whether this country alone is driving the behavior of other donors. Although positive, the coefficient of interest is smaller in magnitude and significant only at the 10% level. It thus indicates that donors are not simply reacting to a single influential actor, the United States, but rather that donor leadership is context-specific.

Finally, in column 7, as an additional placebo test, we examine how donors react to Sweden, a country which, despite being an active and important provider of international assistance (and the fourth most frequent donor in our sample) is widely accepted as a neutral, "good" donor that provides "aid predominantly based on humanitarian motives" (Dreher and Fuchs, 2015, p.1013). As expected, donors do not follow Sweden differentially based on their overlap in terms of exports to recipient countries.

Taken together, our main finding that competition over export goods accelerates aid giving is robust to various alterations of our regression model and is not consistent with alternative interpretations such as informational similarity.

3.4 Mechanisms

Table 5 – Lead Donors and Commercial Competition: Mechanisms

	Dependent Variable: *Aid*				
	(1)	(2)	(3)	(4)	(5)
ESI Lead	0.036	0.191	0.052	0.068**	0.055*
	(0.029)	(0.152)	(0.077)	(0.026)	(0.031)
ESI * Aid Lead	0.136**	0.255	0.360***	0.024	0.185***
	(0.066)	(0.163)	(0.074)	(0.114)	(0.062)
H(Daycount)	Yes	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Emergency FE	Yes	Yes	Yes	Yes	Yes
Donor FE	Yes	Yes	Yes	Yes	Yes
Emergency-Day FE	Yes	Yes	Yes	Yes	Yes
Sample	Cash	In Kind	Govt-to-Govt	Govt-to-IO	G20 Donors
N	8964	1943	2761	7789	4377

Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Two-way clustered (at donor and recipient level) standard errors in parentheses. All regressions include weekday, day of the month, month, donor and emergency fixed effects, and a 3rd-order polynomial function of the number of days passed between disaster start and each donor's decision to provide first assistance. Baseline results using 3-day window after decision day.

[43] For more information on strategic goods, see https://www1.defence.gov.au/business-industry/export/controls/export-controls/defence-strategic-goods-list and https://op.europa.eu/en/publication-detail/-/publication/08fdab5f-9766-11e7-b92d-01aa75ed71a1/language-en (accessed June 2021).

In Table 5, we run additional regressions to explore the mechanisms driving our main finding. In addition to the timing of the aid decision, donors must also choose the type of assistance they provide—cash or in kind—and through which channel it is funnelled, i.e., directly to the recipient government or via other organizations, including international governmental organizations (IOs) and non-governmental organizations (NGOs). As acknowledged by the aid allocation literature (e.g., Cassen, 1986, Dollar and Levin, 2006, Raschky and Schwindt, 2012), these choices too are likely to depend on donors' strategic interests and reflect, among other considerations, how much discretion and flexibility they entrust recipient countries with. Thus, "[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), since these are usually preferred by recipient countries for being less restrictive. Therefore, if donors are competing with the lead donor with the goal of securing their commercial interests in the recipient country, we should expect them to choose the aid modality that is more likely to please its beneficiary. As columns 1 to 4 show, this is exactly what we observe. Our main finding is driven by financial aid rather than in-kind aid and government-to-government aid rather than aid delivered through IOs and NGOs. Moreover, the fact that we do not observe an effect for in-kind assistance rules out the alternative explanation that donors with more similar export structures in recipient countries are more likely to follow each other simply because they have more similar logistical infrastructure in place in the recipient country.

Lastly, we test whether export competition is even stronger an incentive among G20 donors, as these are powerful countries with largest economies and are thus in a privileged position to set their commercial agendas. The results in column 5 show indeed larger effects for this group of donors.

4 Conclusion

Although much has been written about what determines the allocation of emergency relief (e.g., Drury et al., 2005, Fink and Redaelli, 2011, Raschky and Schwindt, 2012), far less attention has been dedicated to one of the most important prerequisites for its success: the speed of its provision. Donor countries differ substantially in terms of how fast they respond to (fast-onset) natural disasters, and we provide novel evidence that some of these variations are systematic and not driven only by humanitarian need in disaster-affected countries. Rather, close trade partners and recipients that have conflicting foreign-policy preferences receive faster assistance, and so do richer and more democratic countries.

Moreover, the results from our empirical analysis at the day level highlight the powerful influence donors have on each other. On the one hand, we observe that, whenever leading donors decide to provide assistance, they encourage their peers to quickly follow suit. In the context of humanitarian relief, this shows that lead 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 strengthened by their own agendas, and in particular by an effort to secure their export markets. The more donors compete over exports to a given recipient country, the faster they respond to each other.

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.[44] Second, based on the ethical principles of humanitarian law, emergency aid has been devised as a tool to provide quick relief to countries at times of great vulnerability and, to a much greater extent than development

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

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 distress.[45]

We acknowledge several limitations of our analysis. First, we lack information on the actual delivery date and are thus confined to an analysis of commitment dates. Although aid commitments are legally binding, information on the day the aid flow arrives at the disaster-affected area would 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, 2020). 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 aid activities. 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.

[45] 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). However, on the positive side, it may also reduce the likelihood of negative (development) 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.

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Appendix

Additional Correlates of the Speed of Aid

In addition to the bilateral characteristics discussed in Section 2, we also analyze whether the variation in our measure of aid speed, *Duration*, is explained by recipient and donor characteristics.

A.1 Recipient Characteristics

The economic variables of interest in this case are recipient's GDP per capita (in logarithmic form) and trade (exports and imports) as a percentage of GDP—both taken from WDI. The former is not only a a measure of a country's economic importance, but also reflects its self-aid capacity.[46] The latter is a measure of trade openness, which we expect to be positively correlated with the speed of aid.

To capture donor's political interests in the disaster-affected country, we add a dummy variable that takes a value of one if a recipient is a temporary member of the UNSC. In line with Dreher et al. (2009*a*,*b*), we expect donors to engage in vote-trading activities and thus to provide faster aid to UNSC members. Note, however, that a positive coefficient could be simply explained by the fact that disaster-struck UNSC members can arguably communicate their humanitarian needs to a greater audience of potential donors and thus mobilize faster disaster aid (again, see Dreher et al., 2009*a*,*b*). Moreover, we add recipient's UNGA ideal point to account for its foreign-policy preferences.

We include, in addition, an index that reflects the quality of electoral democracy in the recipient country.[47] On the one hand, (democratic) donors may be more likely to provide aid to democracies faster in order to support the recipient's institutions. On the other hand, donors could also favor autocracies if they believe that countries with such a regime are less capable to handle disasters by themselves (see Sen, 1991).[48] Moreover, aid effectiveness could differ in democracies and autocracies. Accordingly, Plümper and Neumayer (2009) find that, in the context of famines, autocracies need much more aid to reduce mortality. Finally, donors guided by commercial interests could provide faster support to autocracies to buffer trade reductions. As the evidence presented by Gassebner et al. (2010) suggests, trade with autocracies suffers more from disasters than commercial relationships of democracies.

There are several reasons to believe that the speed with which a country receives aid depends also on its institutional characteristics. For instance, donors may reward recipient merit (see Öhler et al., 2012) and, if this is the case, countries with a lower level of corruption should be more likely to receive timely support after a catastrophe. Besides, donor decisions may take recipients' institutional capacity into account and thus provide faster emergency aid to counteract the reduced self-aid capacity. More specifically, donors may anticipate that their humanitarian aid takes longer to arrive at the final destination in countries with high levels of corruption and thus donate faster to ensure prompt delivery. To at least partially capture these phenomena, we include a measure of control of corruption as a proxy of institutional quality (Kaufmann et al., 2009).[49]

We follow Raschky and Schwindt (2012) and use population size (in logarithmic form) as a further control for the socioeconomic environment.[50] Finally, this setting allows us to include disaster-type,

[46]A positive coefficient for recipient GDP per capita would not necessarily indicate foul intentions by donors, as poorer recipient countries are likely more difficult to reach.

[47]V-DEM's Electoral democracy index.

[48]Most of the 45 donors in our sample are democracies.

[49]The control of corruption index "[r]eflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as 'capture' of the state by elites and private interests" (Kaufmann et al., 2009).

[50]We had also included population density as an additional control variable, as different predictions

donor-year, donor-disaster-type, recipient, and donor-recipient fixed effects.

A.2 Donor Characteristics

Finally, we analyze whether also donor characteristics are relevant to explain the speed of humanitarian assistance. Similarly to the recipient-level analysis, we include (the logarithm of) donor GDP per capita and trade as a percentage of GDP, as we expect donors that are richer and more active in international trade to provide aid faster—either because of self-interest or because they are in a position to act quicker. Besides, we also include donors' UNGA ideal point to account for political alignment.

Furthermore, we control for the size of donor population (in logarithmic form), and for the quality of donor democratic institutions. Donor population size proxies donor countries' aid capacity, which we thus expect to be negatively associated with decision time. With respect to the regime type of donors, decision-making processes in authoritarian donor countries are less constrained by veto players than in democracies, where checks and balances may slow down decisions. In Saudi Arabia and Morocco, for example, the king decides whether to provide emergency aid.[51] At the same time, the need to satisfy veto players and different opinions represented in legislature and government could lead to quicker decision-making processes as different groups lobby for their interests.[52] Which of these two effects dominates the other is an empirical question.

We include, additionally, a dummy variable indicating whether a donor country is part of the OECD Development Assistance Committee (DAC) in a given year. While all DAC donors endorse the GHD framework and thus the associated timely response requirements, non-DAC donors also highlight the rapidity of their response and emphasize their reaction time as being a key point of distinction with their DAC counterparts (Harmer and Martin, 2010). Non-DAC donor Israel, for example, claims that "[n]o other country can dispatch search and rescue teams and field hospitals as fast and effectively."[53] Similarly, India's government highlights its speedy assistance, which is tied to the country's ambition for increasing international visibility (Meier and Murphy, 2011). While the comparative advantage of DAC donors may lie in their significant experience with aid delivery, non-DAC donors might be able to decide on aid provisions in a more flexible manner given their independence from a regulatory aid framework or the need for coordination with other donors (see ECOSOC, 2008, for a discussion).[54] At the same time, however, most non-DAC donors do not have dedicated facilities or capacities to quickly disburse funds after a shock. We include also emergency, donor, donor-disaster-type and donor-recipient fixed effects.

With respect to recipient characteristics, the results in Table 6 show that not only need (measured by the total number of people killed by each disaster) explain aid speed. Our findings show that when disasters hit places that are richer and more democratic, it takes on average fewer days for donors to

exist with regards to its effect on humanitarian response (see Fink and Redaelli (2011)). On the one hand, densely populated areas may be in larger need of assistance as a greater density complicates evacuation of survivors, and may thus facilitate the spread of infectious diseases. On the other hand, areas with high population density may possess better networks that ease rescue efforts after a disaster. Nevertheless, it did not seem to play a role for the speed of aid.

[51]See Al-Yahya and Fustier (2011) for an overview on Saudi Arabia's humanitarian aid.

[52]See Round and Odedokun (2004) for a discussion of the role of checks and balances on aid effort.

[53]Israel also claims that its "200-strong relief team was the first on the scene in January 2010 after the earthquake hit Haiti" and that it "was one of the first countries to send aid according to the needs and request of the Japanese government" after the 2011 earthquake. See website of Israel's Ministry of Foreign Affairs, available at: `https://mfa.gov.il/MFA/ForeignPolicy/Aid/Pages/default.aspx` (accessed February 2021).

[54]India, for example, lacks a common humanitarian aid policy. Meier and Murphy (2011, p.11) describe the country's humanitarian aid bureaucracy as "organically grown" with decisions made "in an ad hoc manner" and "on a case-by-case basis." They conclude that "such a flexible set up enables India to [. . .] provide aid quickly".

commit to their first aid flow. Although this could be an indication of favoritism, it may just as well be the case (not necessarily less problematic) that these countries, due to being more developed, are simply able to vent their needs faster and more effectively. Nevertheless, it is remarkable that the result for democracy survives (and actually increases in magnitude after) the inclusion of donor-recipient fixed effects.

Table 6 – Correlates of the Speed of Aid (Recipient)

	Dependent Variable: *Duration (log)*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(R) Trade (%GDP)	0.0009	0.0008	0.0012	0.0007	0.0066	0.0074	0.0096*	0.0095*
	(0.0011)	(0.0013)	(0.0012)	(0.0013)	(0.0051)	(0.0051)	(0.0048)	(0.0049)
(R) UNSC	-0.1060	-0.0539	-0.0733	-0.0121	-0.2395	-0.1214	-0.3103*	-0.3154*
	(0.1180)	(0.1297)	(0.1192)	(0.1344)	(0.1678)	(0.1662)	(0.1536)	(0.1567)
(R) UNGA Ideal Point	-0.0391	-0.0105	-0.0377	-0.0211	0.0723	0.2112	0.0895	0.1725
	(0.0908)	(0.0831)	(0.0900)	(0.0812)	(0.2659)	(0.2348)	(0.2854)	(0.2696)
(R) Democracy Index	-0.5139**	-0.6991***	-0.5213**	-0.6921***	-1.2046*	-1.7837**	-1.3687**	-1.8939**
	(0.2237)	(0.1881)	(0.2256)	(0.1909)	(0.6576)	(0.6402)	(0.5910)	(0.6530)
(R) GDP p.c. (log)	-0.2085***	-0.1855**	-0.2158***	-0.1897**	-0.5934	-0.8045	-1.5431**	-1.0983
	(0.0724)	(0.0674)	(0.0731)	(0.0686)	(0.7530)	(0.8266)	(0.6777)	(0.6287)
(R) Corruption index	0.2470**	0.2374***	0.2433**	0.2353**	-0.2167	-0.3141	-0.3020	-0.3780
	(0.0960)	(0.0811)	(0.0967)	(0.0829)	(0.2677)	(0.3133)	(0.2695)	(0.3376)
(R) Population (log)	0.1002***	0.1082***	0.1039***	0.1036***	3.2064*	2.2174	2.9308	2.7325
	(0.0227)	(0.0244)	(0.0233)	(0.0264)	(1.7946)	(1.9516)	(1.9555)	(2.0857)
Total killed (log)	-0.1343***	-0.1303***	-0.1444***	-0.1357***	-0.1492***	-0.1338***	-0.1755***	-0.1483***
	(0.0164)	(0.0185)	(0.0168)	(0.0177)	(0.0144)	(0.0188)	(0.0183)	(0.0209)
Disaster-type FE	Yes	Yes	No	No	No	No	No	No
Donor-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Donor-Disaster FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Recipient FE	No	No	No	No	Yes	Yes	No	No
Donor-Recipient FE	No	No	No	No	No	No	Yes	Yes
Only G20 Donors	No	Yes	No	Yes	No	Yes	No	Yes
N	2404	1250	2370	1234	2360	1218	1444	882

Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Two-way clustered (at donor and recipient level) standard errors in parentheses. Dependent variable: *Duration* (log).

Lastly, as reported in Table 7, donor characteristics provide a more nuanced picture. In addition to the clear positive relationship between country size (in terms of population) and aid speed, among the subsample of G20 donors, we find that countries with foreign-policy preferences that are more liberal, or Western, are on average significantly slower to provide assistance. In fact, according to column 8, increasing a donor ideal point by one standard deviation would slow its aid provision by almost 80%. Moreover, our results indicate that DAC donors are faster, and more democratic donors are, if anything, slower to provide relief.

Table 7 – Correlates of the Speed of Aid (Donor)

	Dependent Variable: *Duration (log)*							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(D) DAC	-0.1669	-0.3921**	-0.2982*	-0.5747***	-0.3262*	-0.6024***	-0.2176	-0.5248
	(0.1186)	(0.1726)	(0.1556)	(0.1961)	(0.1660)	(0.1887)	(0.3862)	(0.3891)
(D) Trade (%GDP)	-0.0000	0.0026	0.0025	0.0121**	0.0037*	0.0110**	-0.0005	0.0199**
	(0.0005)	(0.0025)	(0.0019)	(0.0044)	(0.0020)	(0.0050)	(0.0033)	(0.0071)
(D) UNGA Ideal Point	-0.0505	-0.0381	0.0830	0.4781***	0.1202	0.5714***	0.3062	0.7023***
	(0.0532)	(0.0587)	(0.1894)	(0.1010)	(0.2185)	(0.0953)	(0.2777)	(0.1927)
(D) GDP p.c. (log)	-0.1029	-0.0323	-0.2036	0.3755	-0.1744	0.3330	-0.1746	0.9831
	(0.0705)	(0.0858)	(0.3586)	(0.4544)	(0.3683)	(0.4127)	(0.4859)	(0.7455)
(D) Democracy Index	-0.2614	-0.1317	1.0738	0.5364	0.6516	0.0326	1.5978	3.6243**
	(0.2369)	(0.2921)	(1.1192)	(1.0231)	(1.1197)	(1.0888)	(1.9208)	(1.3425)
(D) Population (log)	-0.1219***	-0.0749	-1.5068***	-1.6754**	-1.2780***	-1.3223***	-2.5617***	-3.3163**
	(0.0372)	(0.0433)	(0.4353)	(0.7359)	(0.4359)	(0.4262)	(0.7239)	(1.4999)
Emergency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Donor FE	No	No	Yes	Yes	No	No	No	No
Donor-Disaster FE	No	No	No	No	Yes	Yes	Yes	Yes
Donor-Recipient FE	No	No	No	No	No	No	Yes	Yes
Only G20 Donors	No	Yes	No	Yes	No	Yes	No	Yes
N	2737	1345	2737	1345	2708	1333	1672	879

Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Two-way clustered (at donor and recipient level) standard errors in parentheses. Dependent variable: *Duration* (log).

Figure 4 – Average and Median Duration across Disasters over Time

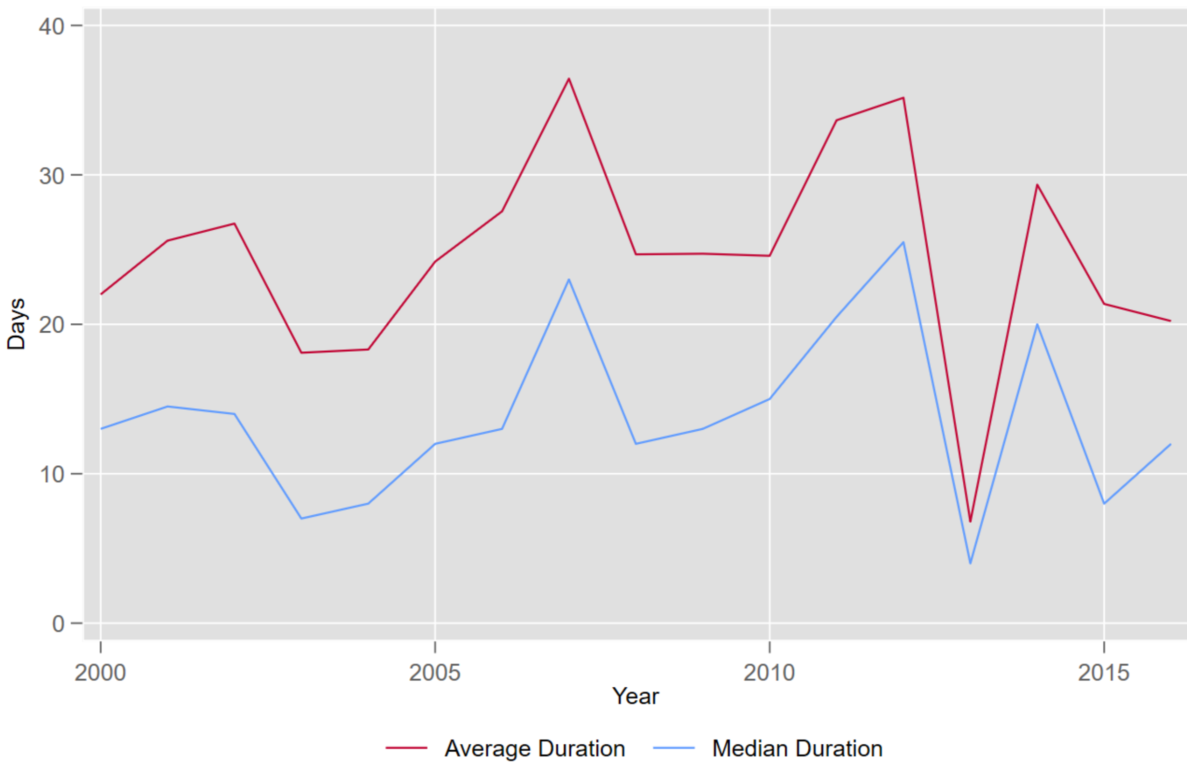


Table 8 – List of Donors

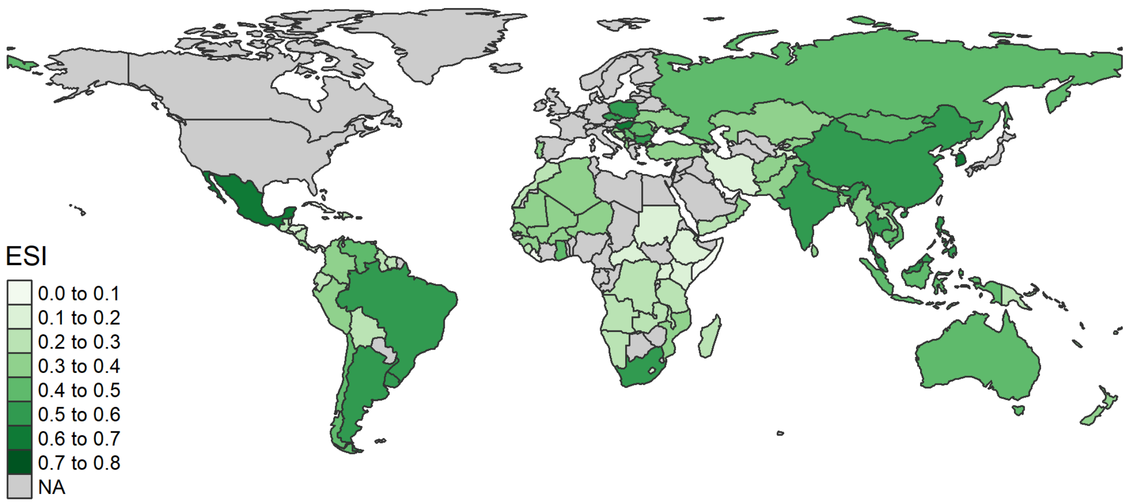
	No. of contributions	Total amount contributed (USD million)	Average duration (days)
Argentina	20	0.10	24.40
Australia	98	53.16	22.40
Austria	46	13.71	34.43
Belgium	50	25.29	33.58
Brazil	31	4.91	23.90
Canada	124	23.78	22.44
China	41	38.71	18.17
Cyprus	19	0.90	56.68
Czech Republic	50	6.74	27.70
Denmark	75	9.24	25.76
Estonia	28	1.89	16.18
Finland	43	15.69	25.70
France	110	31.45	20.10
Germany	178	35.72	28.71
Greece	38	5.91	21.50
Hungary	23	0.75	24.83
India	14	12.22	17.93
Indonesia	8	5.53	10.75
Ireland	78	18.15	30.47
Israel	18	2.82	17.17
Italy	116	27.87	22.00
Japan	153	27.36	15.23
Korea, Republic of	67	9.67	20.96
Luxembourg	96	10.23	37.24
Monaco	24	1.65	50.42
Netherlands	66	40.62	26.55
New Zealand	67	20.18	26.13
Norway	124	37.78	33.07
Poland	23	2.00	19.87
Portugal	17	3.03	19.06
Russian Federation	34	40.84	17.88
Saudi Arabia	47	513.06	35.77
Singapore	38	1.21	24.61
Slovakia	18	5.22	19.28
Slovenia	19	1.23	14.37
South Africa	11	0.93	26.73
Spain	95	53.36	21.62
Sweden	146	27.72	27.68
Switzerland	97	22.49	39.21
Thailand	18	1.10	19.22
Turkey	61	57.64	33.31
United Arab Emirates	55	19.43	41.13
United Kingdom	86	68.58	25.60
United States	295	54.38	20.71
Venezuela	21	0.42	20.90

Table 9 – Descriptive Statistics

	Disaster-Level Analysis				
	mean	sd	min	max	count
Duration (days)	25.91	31.01	1.00	178.00	2,886
Total killed (log)	5.03	3.04	0.00	12.31	2,886
(R) Trade (%GDP)	66.02	32.54	0.17	277.14	2,693
(R) UNSC	0.09	0.28	0.00	1.00	2,886
(R) UNGA Ideal Point	-0.45	0.60	-2.07	2.33	2,822
(R) Democracy Index	0.49	0.22	0.08	0.91	2,745
(R) GDP p.c. (log)	7.62	0.99	5.46	10.85	2,814
(R) Corruption index	-0.54	0.60	-1.72	2.34	2,881
(R) Population (log)	16.89	1.99	9.30	21.01	2,878
(D) Trade (%GDP)	83.10	67.49	19.80	437.33	2,862
(D) UNGA Ideal Point	1.06	0.84	-1.37	2.94	2,871
(D) GDP p.c. (log)	10.50	0.71	6.77	12.15	2,886
(D) Democracy Index	0.81	0.20	0.02	0.92	2,862
(D) Population (log)	17.03	1.76	10.38	21.04	2,886
Exports, D to R (log)	13.39	3.16	0.00	20.99	2,814
Imports, from R to D (log)	12.96	3.72	0.12	22.00	2,765
UNGA delta	1.58	0.88	0.00	4.36	2,808
Distance (log)	8.78	0.70	5.63	9.88	2,853
Common language	0.16	0.37	0.00	1.00	2,853

	Daily Analysis				
	mean	sd	min	max	count
Aid	0.04	0.19	0.00	1.00	74,780
Aid Lead (3d)	0.01	0.12	0.00	1.00	129,780
Aid Lead (7d)	0.03	0.17	0.00	1.00	129,780
Aid Lead (30d)	0.14	0.34	0.00	1.00	129,780
ESI Lead	0.07	0.16	0.00	0.75	519,480
ISI Lead	0.08	0.19	0.00	0.95	519,480
PSI Lead	0.76	0.20	0.00	1.00	129,240
InfoSI Lead	0.85	0.18	0.00	1.00	105,480
Aid USA (3d)	0.01	0.12	0.00	1.00	519,480
ESI USA	0.28	0.19	0.00	0.75	519,480
Aid SWE (3d)	0.01	0.10	0.00	1.00	519,480
ESI SWE	0.25	0.18	0.00	0.84	519,480

Figure 5 – Export and Import Similarity Indices of Japan and the United States (2000-2016 Average)



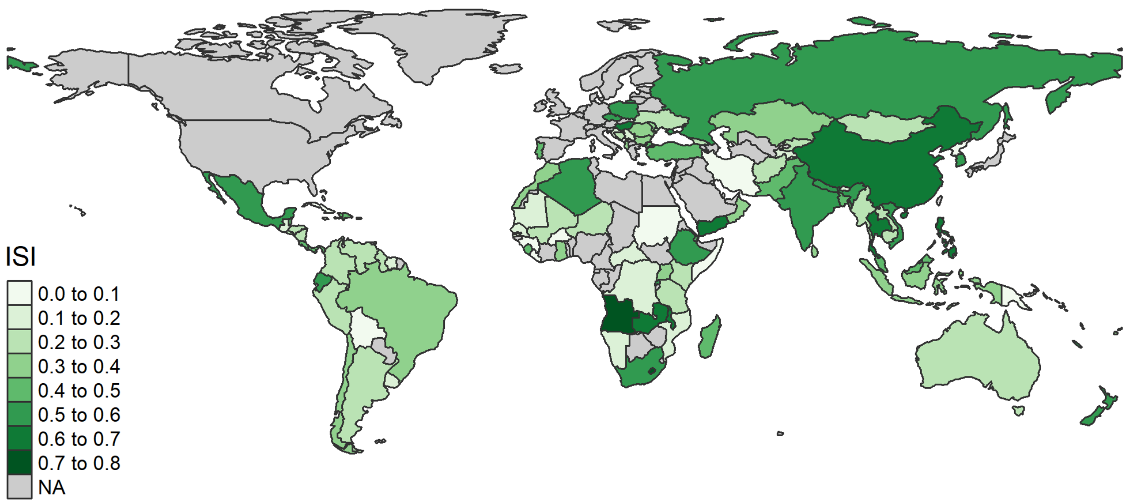
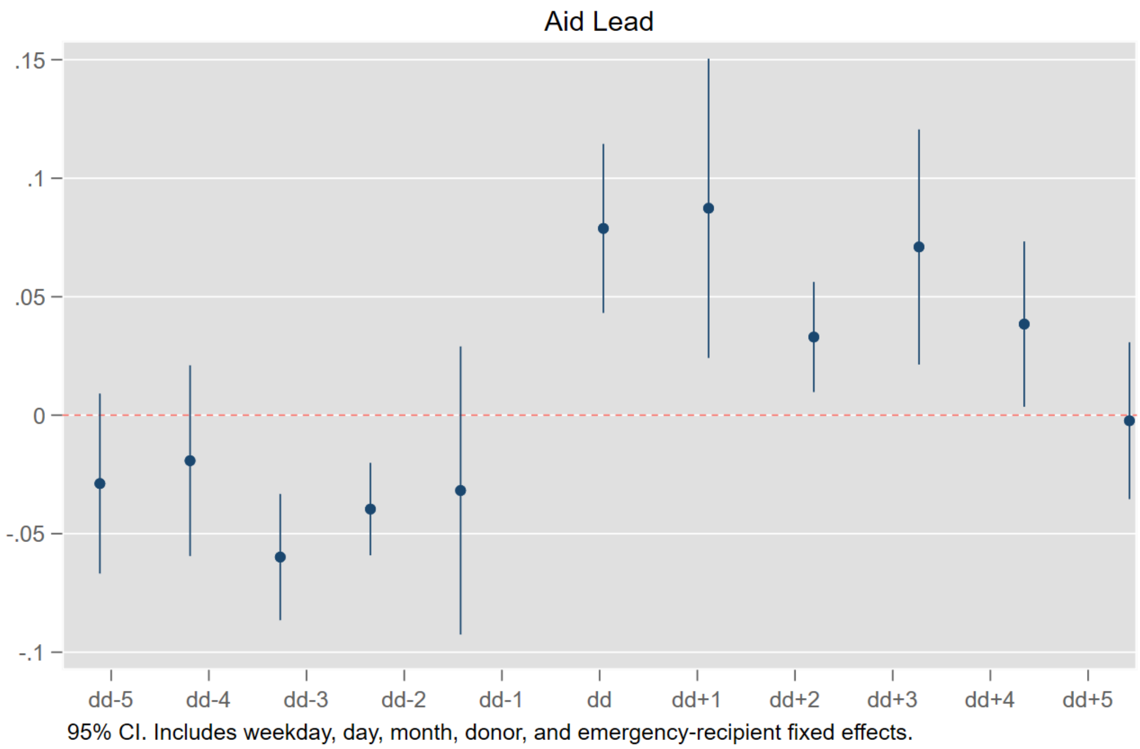


Figure 6 – Lead Donors: Various Reaction Windows



Coefficient for Aid Lead with different time windows. Regressions include weekday, day-of-the-month, month, donor, and emergency fixed effects. 95% confidence intervals.