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Foreign Aid and (Big) Shocks: Evidence from Natural Disasters

Rabah Arezki, Youssouf Camara, Patrick Imam, Kangni Kpodar

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ABSTRACT: We explore the effect of (big) shocks on the allocation of (bilateral) aid using natural disasters as natural experiments. We find that aid commitment statistically significantly increases following natural disasters, and that humanitarian aid precedes structural aid. While we find that the average effect is quantitatively significant, poorest countries or countries faced with most damaging natural disasters do not receive the most aid. We find no evidence that foreign aid commitment disburses faster following natural disasters. Further explorations into the mechanisms driving aid in disaster countries point to the importance of political alignment with (major) donors in recipient countries with low state capacity.

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Author's E-Mail Address:	rarezki.econ@gmail.com; camarakantona@gmail.com; pimam@imf.org; kkpodar@imf.org

*Rabah Arezki is a Director of Research at CNRS, a Senior Fellow at FERDI and Harvard's Kennedy School of Government. Youssouf Camara is a postdoctoral fellow at McGill University. Patrick Imam and Kangni Kpodar are Economists at International Monetary Fund (IMF). We thank Andy Berg, Gabriela Cugat, Bill Easterly, Patrick Guillaumont, Honore Ndoko, Ha Nguyen, Philippe Le Houérou, Adnan Mazarei, and Baoping Shang Petia Topalova for insightful comments. This research is part of a Macroeconomic Research in Low-Income Countries project [Project ID: 60925] supported by the UK's Foreign, Commonwealth and Development Office (FCDO). The findings, interpretations, and conclusions expressed in this paper do not necessarily reflect the views of IMF, the Executive Directors of IMF or the governments they represent, and the FCDO.

WORKING PAPERS

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1. Introduction

Notwithstanding the stated goals of foreign aid to support economic development in recipient countries, the actual drivers of aid allocation have been the subject of intense academic scrutiny with some authors pointing to the importance of donor-recipient political alignment.[1] The generally accepted definition of foreign aid relates to transfers provided by governments in concessional terms to achieve economic development goals. However, the jury is still out on whether the allocation of aid is driven by characteristics emanating from either donors or recipients (or both). Because of their potential economic and social consequences on aid recipient countries, exogenous shocks can help reveal the mechanisms driving the response of foreign aid whether they are related to donors or recipients' characteristics. Simply put, natural experiments provide an exogenous source of variation to further explore the effect of (big) shocks on aid allocation. In the present paper, we explore the effects of (big) shocks on the allocation of aid using disasters as natural experiments.

To the extent of our knowledge, there are very few papers exploiting natural experiment to dissect the effect of (big) shocks on foreign aid allocation.[2] [3] A notable exception is Faye and Niehaus (2012) who document the existence of "aid cycle", whereby donors strategically use bilateral aid to sway the outcome of elections. In other words, the authors exploit the timing of (predetermined) elections to explore whether donors behave strategically during elections. In this paper, we follow a similar empirical approach to identify the effect of natural disasters on foreign aid.[4]

Disasters such as earthquakes, landslides, and hurricanes are typically considered as natural experiments. Specifically, the timing of natural disasters is arguably exogenous. In contrast, the extent of damages—stemming from the combination of intensity of the shocks and the exposure of the country facing the shock—caused by natural disasters cannot be argued to be exogenous. In other words, the intensity of natural disasters is arguably exogenous but the exposure to these shocks is endogenous. For these reasons, this paper exploits chiefly the timing of natural disasters for identification purposes. In turn, that allows for the identification of the causal relationship between shocks and the allocation of aid. Natural disasters are also salient shocks. The consequences stemming from natural disasters on physical infrastructure and human capital can be significant. The 2010 earthquake which stroke Haiti, one of the world's poorest countries, is a case in point.[5] The death toll amounted to an estimated 220,000 individuals with 300,000 injured and 1.5 million homeless.[6] Losses and damages were estimated at US$7.3 billion, equivalent to 120 percent of GDP. While we rely mostly on the timing of natural disasters for identification, the salient nature of the shock could potently shift the behavior of donors pertaining to the allocation of aid. The significance of the response of foreign aid resulting from the salience of natural disasters could also be affected by recipient countries' state ability to absorb aid. On the one hand, foreign aid could increase precisely to alleviate weakness in state capacity also considering countries with low state capacity tend to be the most affected by natural disasters (IMF, 2019). On

[1] See Easterly (2007) for a powerful criticism of the development aid industry arguing that Western donors' attempt to transplant institutions to the developing world has failed. Also importantly, Faye and Niehaus (2012) document the existence of "political aid cycle" whereby donors use aid to influence the outcome of elections.

[2] Becerra et al. (2014) provide early evidence related to the response of aid flow following natural disasters. The authors find no evidence of aid reallocation between countries.

[3] Interestingly, Werker et al. (2009) utilize oil price fluctuations as an exogenous source of variation to examine the macroeconomic implications of foreign aid from the Organization of Petroleum Exporting Countries (OPEC). The study reveals that aid substitutes for domestic savings, does not significantly impact the financial account, and leads to substantial unaccounted capital flight, challenging conventional assumptions about the economic benefits of foreign aid.

[4] A related paper by Eisensee and Stromberg¨ (2007) documents that public opinion in the United States is influenced by media coverage of global events and disasters and in turn affect U.S. aid decisions. The authors also find that global events outside natural disasters tend to crowd out US disaster relief.

[5] See URL link to the article referencing the salient facts about Haiti 2010 earthquake: https://www.britannica.com/event/2010-Haiti-earthquake/Humanitarian-aid

[6] See URL link on United Nations' report on the death toll of the Haiti 2010 earthquake: https://news.un.org/en/story/2022/01/1109632#:~:text=On%2012%20January%202010%2C%20a,%2C%20known%20as%20MINUSTAH%2C%20collapsed

the other hand, donors could be reluctant to send more aid to countries with low state capacity for fear that it would be wasted. That is an empirical question we address in this paper.

The Haiti example also reveals that (big) shocks can shift both the volume and composition of aid toward recipient countries affected by natural disasters. Not surprisingly, the initial flow of aid was composed of mostly humanitarian aid to address the pressing needs of the population. Initially, the donor community pledged US$9.9 billion of aid, with the additional goal of spending most of the aid in the first few years following the earthquake. However, a sizable share of the pledges was cancelled. Figure 1 shows bilateral and multilateral aid commitments which both peaked in the year 2010 which corresponds to the timing of the natural disaster which stroke Haiti. Only half of the remaining commitments were disbursed in the first two years. Critics have also observed that the aid response lacked coordination between different organizations and that donors also failed to involve local authorities. Crane et al. (2010) point out that donor leverage was used to dictate terms of engagement on account of the alleged risk of corruption—and weak state capacity—with little consideration for domestic politics. The example of Haiti is telling about the nature of the aid response following natural disasters and raises important empirical questions: Is the volume of aid allocated following natural disasters significant? How is the composition of aid impacted? Are aid commitments disbursed faster following natural disasters? Are all low state capacity countries equally receiving more aid inflows in the face of natural disaster countries?

To explore systematically the relationship between foreign aid and natural disasters, we use a gravity model of aid from (bilateral) donors for the period going from 1995 to 2021. We exploit data from the International Disaster Database (EM-DAT) to capture the timing of and damages associated to natural disasters. EM-DAT contains data on the occurrence and impacts of mass disasters of all types worldwide. We combine the EM-DAT dataset with data on aid namely ODA. Data on ODA flows are provided by the 29 OECD members of the Development Assistance Committee (DAC). We exclusively use bilateral aid–as opposed to multilateral aid—which accounts for about 75 percent of overall aid globally according to the Dube and Naidu (2022). In this paper, we leave out from our analysis multilateral aid which is pooled from multiple countries. Hence multilateral aid cannot be attributed to one single donor country.[7]

It should however be noted that the United Nations play an important coordinating role in disaster relief. Other multilateral organizations such as the Bretton Woods institutions do play important emergency finance and reconstruction roles following natural disasters. Whilst the bilateral aid data used in our analysis cover most of the foreign aid, our results should however not be interpreted as reflecting multilateral aid response to natural disasters. That said, the response of multilateral donors to natural disasters is likely a reflection of the main (bilateral) donors' response. Figure 1 presents the evolution of aid commitments to Haiti from both bilateral and multilateral sources. Figure 1 shows that bilateral and multilateral aid flows do move in sync especially following the 2010 earthquake. What is more is that the amount related to bilateral aid flows is also far greater than multilateral flows.

We find that aid commitment statistically and economically significantly increases following natural disasters, and that humanitarian aid precedes structural aid. However, we find that poorest countries or countries faced with most damaging natural disasters do not receive the most aid. We also do not find evidence that foreign aid commitment disburses faster following natural disasters. Further explorations into the mechanisms driving aid in disaster countries point to the importance of low state capacity and political alignment with donors for recipients' countries.

[7] Regression analysis of the ratio between multilateral and bilateral aid flows following natural disasters point to no statistically significant effect. Results are not presented in the paper but are available upon request.

Our paper is also related to the strand of literature on the effectiveness of foreign aid.[8] The subject of aid allocation and aid effectiveness are intertwined. A notable paper by Burnside and Dollar (2000) point to the importance of "good policies" defined as policies which are good for growth as a driver of aid effectiveness. The authors further argue that aid allocation is only weakly going to countries with good policies. In turn, the authors argue that this needs to change to increase the effectiveness of foreign aid. Easterly (2003) provides evidence that the impact of aid on growth is inconclusive and depends on a variety of factors including policies. A more recent paper by Andersen et al. (2022) shows evidence of outright aid capture in low-income countries. The authors find aid disbursements to highly aid-dependent countries coincide with sharp increases in bank deposits in offshore financial centers known for bank secrecy and private wealth management but not in other financial centers. In this paper, we do not take on the issue as to whether aid following natural disasters is used effectively. We however document the response of the volume aid and the shift in composition of aid resulting from natural disasters. We also test whether donor or recipient characteristics such as political alignment and state capacity matter in driving the response of foreign aid.

Our results are also related to the line of enquiry on climate dynamics and the economic consequences of climate change and natural disasters. Several papers and scientific reports have documented the link between climate change and natural disasters. For instance, Emanuel (2005) shows that climate change through increased temperature causes more intense and frequent hurricanes. The author argues that the results suggest that future warming may lead to an upward trend in tropical cyclone destructive potential, and a substantial increase in hurricane-related losses in the twenty-first century.[9] Indeed, several authors have documented the consequences of natural disasters on physical infrastructure, output loss and employment.[10] Prominently, Dell et al. (2012) examine the economic impacts of climate change on agricultural output. The authors provide empirical evidence on the relationship between weather fluctuations and economic outcomes.[11] Our paper contributes to these strands of literature by documenting the change in volume and composition of aid allocation following the intensification and rising frequent of natural disasters (see Figure 2). Indeed, our results suggest that the aid response to natural disasters is economically significant, and that foreign aid is becoming more humanitarian hence more reactive. In turn, that could crowd out structural aid hence aggravating countries' exposure to natural disasters. Our results have important implications for the sustainability of the aid industry.

The remainder of the paper is organized as follows. Section 2 describes data sources. Section 3 discusses the empirical strategy. Section 4 presents the results. Section 5 lays out extensions and robustness checks. Section 6 concludes.

2. Data

In this section, we present our data set which consists primarily of data on foreign aid as well as natural disasters. We also present additional data for control variables as well as data on political alignment and state capacity. Table 1 presents a summary of descriptive statistics.

Foreign aid is our main dependent variable. Foreign aid data known as ODA cover the period going from 1975 to 2021. ODA is retrieved from OECD Development Cooperation Directorate (DAC) database. We exclusively

[8] Dollar and Alesina (2000), Alesina and Weder (2002) and Knack (2001) are amongst the early contribution to the strand of literature on aid allocation. The authors find that foreign aid does tend to flow to more democratic and less corrupt countries.

[9] See also IPCC (2014), Titley et al. (2016) and Debarati Guha-Sapir and Below (2017).

[10] See for instance, Cavallo and Noy (2009), Rose and Nagamatsu (2017) and Acevedo Mej´ıa, Villamizar-Villegas, and Garc´ıa-Valencia (2019). Interestingly, Stromberg (2007) discuss the economic impact of natural disasters and the role of humanitarian aid response to disasters.

[11] Dell et al. (2014) for a survey of literature on economic impact of climate change. Burke and Emerick (2016) provide evidence of the effect of climate on agriculture output.

consider bilateral aid flows, excluding multilateral flows. We focus on the 20 largest donors during the study period which together accounted for 99 percent of aid commitments.[12] That results in a 47-year panel dataset, featuring 189 recipients in total, with an average of 165 recipients per donor-year. ODA, as defined by the OECD Glossary, encompasses grants or loans directed to countries and territories classified as “developing” based on criteria such as being official sector undertakings with economic development and welfare enhancement as primary objectives and featuring concessional financial terms. The dataset also incorporates technical cooperation as part of aid, while excluding grants, loans, and credits for military purposes. Importantly, transfer payments to private individuals, such as pensions, reparations, or insurance payouts, are generally not included in the ODA calculation.

Recognizing China’s emergence as a non-traditional creditor donor, a dimension not covered by the OECD’s DAC database, we incorporate data sourced from AidData’s Global Chinese Development Finance.[13] AidData has been constructed through a systematic collection and rigorous quality assurance process for all China’s development projects with the rest of the world. This comprehensive dataset provides an intricate perspective, detailing 13,427 development projects valued at $843 billion. These projects received financing from over 300 Chinese government institutions and state-owned entities, spanning 165 countries across all major global regions during the period from 2000 to 2017. To elucidate, AidData’s Global Chinese Development Finance Dataset meticulously documents the entire spectrum of projects, encompassing those with developmental, commercial, or representational purposes. This extensive repository captures the universe of initiatives supported by official financial commitments. The dataset’s granularity and scope offer a unique lens into the landscape of Chinese development finance.

Natural disaster is our main explanatory variable. Data for natural disasters are from the Emergency Events Database (EM-DAT) by the Centre de recherche sur l’epidemiologie des catastrophes (CRED). The database, compiled from diverse sources including United Nations agencies, non-governmental organizations, reinsurance companies, research institutes, and press agencies, stands as a global repository offering a comprehensive dataset on both natural and technological disasters spanning the globe. Encompassing data from 1900 to the present day, EM-DAT includes records of over 26,000 mass disasters, covering a spectrum of events such as earthquakes, floods, hurricanes, droughts, industrial accidents, and transportation incidents. The expansive coverage, both temporally and across various disaster types, enables a profound understanding of historical patterns and the impacts of disasters, thereby serving as the cornerstone of our empirical analysis. Beyond documenting the occurrence of disasters, EM-DAT extends its scope to include information on the ensuing damage, providing insights into the extent of economic losses, human casualties, and other ramifications. To explore the underlying mechanisms driving aid flows following natural disasters we use a measure of political alignment between major donors and recipients and recipients’ state capacity.

To build our political alignment measure, we use a comprehensive dataset encompassing votes on General Assembly resolutions at the UN from session 49 (1995/1996) to session 75 (2020/2021) compiled by Voelsen et al. (2021). Our alignment measure is based on the average fraction of UN General Assembly votes for which the recipient country and the Group of 7 (G7) donor countries cast concordant votes (either yes, no or abstention). This measure of alignment is calculated for each year of observation between the G7 donor and recipient, and then averaged across all G7 donors to determine the recipient’s alignment. Votes from countries that are absent or not members of the United Nations are excluded, as are projects with no voting mechanism. The state capacity measure captures legal and fiscal elements. Besley and Persson (2009) indeed document the importance of these elements as foundation for the state. In this paper, we use the measure of state to proxy the ability of the state in recipient countries to absorb aid—recall that the definition of aid used in the paper corresponds to transfers to governments. Data are from O’Reilly, Colin, and Ryan H. Murphy (Forthcoming). The index of state capacity is comprehensive, using data from the Varieties of Democracy

[12] China aid flow is also included using an alternative data source discussed further below.

[13] Data are available at the following URL link: https://www.aiddata.org/data/ aiddatas-global-chinese-development-finance-dataset-version-2-0

dataset on fiscal capacity, a state's control over its territory, the rule of law, and the provision of public goods used to support markets. The index is normalized so that it ranges between 0 and 1—to match the range of the political alignment measure.

Additional demographic and economic control variables are obtained from the World Bank's World Development Indicators database (World Bank, 2023). These controls include variables such as population and GDP, allowing us to contextualize our examination within larger socio-economic trends. Population and income in both recipient and donor countries are important determinants of aid commitments. This dataset complements our analysis by providing a broader lens through which to examine the interplay between foreign aid and natural disasters. The inclusion of these controls deepens our understanding, facilitating a more comprehensive examination of the complex relationships between aid and natural disasters.

3. Empirical Strategy

In this section, we describe the empirical strategy to explore the effects of natural disasters on foreign aid commitments. To do so, we exploit the specific timing of natural disasters which are arguably exogenous, to test whether foreign aid commitments change. We follow the reduced-form specification used by Faye and Niehaus (2012). In all our specifications, we incorporate donor-recipient fixed effects, allowing us to estimate the effects of disasters by relying solely on the time variation within donor-recipient pairs. This approach effectively eliminates any time-invariant characteristics associated with recipients and their specific bilateral relationships with donors. Our approach is akin to a difference-in-difference estimation using aid inflows (outcomes) for countries who were exposed to natural disasters (treated) and countries which were not (not treated), both before and after disasters.

To account for the potential influence of trends in aid flows coinciding with natural disasters, we introduce year fixed effects, donor-year fixed effects, and time-varying controls such as population and GDP. That approach helps mitigate the risk of confounding variables and ensures a robust examination of the effects of natural disasters on bilateral aid.

Formally, let d index donor countries, r index recipient countries, and t index years. We estimate the direct relationship between bilateral aid and natural disasters within a country pair:

$$ODA_{drt} = \theta NAT_{rt} + X'_{drt}\beta + \gamma_{dr} + \epsilon_{drt} \qquad (1)$$

where ODA_{drt} is the logarithm of commitment ODA from donor d to recipient r at time t; and NAT_{rt} is the dummy that takes 1 if country r has any natural disasters in year t or the logarithm of the overall damage value in US dollars at the time t of the natural disasters in the recipient country r; X'_{drt} is a vector of time-varying donor or recipient specific control variables such as GDP and population, or year or donor-year fixed effects; and γ_{dr} represents a vector of donor-recipient country pair fixed effects.

Further, we explore the mechanisms driving aid allocation following natural disasters, exploring the role of political alignment and absorptive capacity. Indeed, political alignment is expected to interact with natural disasters to drive more aid commitments and so does absorptive capacity, proxied here by state capacity. To explore these mechanisms and understand which one dominates, we augment Equation (1) with a variety of interactions, including between natural disasters and political alignment, and between major donors and recipient (UN_{drt}) as shown in Equation (2). For simplicity, we only present the use of one interaction term between natural disasters and political alignment. In our regression analysis, we also include the interaction term between natural disasters and state capacity, as well as the double interaction term between natural disasters as well as political alignment and state capacity.

$$ODA_{drt} = \theta_1 NAT_{rt} + \theta_2 UN_{drt} + \theta_3 NAT_{rt} * UN_{drt} + X'_{drt}\beta + \gamma_{dr} + \epsilon_{drt} \quad (2)$$

Bilateral aid flows between a specific donor and recipient over time involves in numerous instances zero values. Most empirical studies typically adopt a straightforward approach of excluding pairs with zero aid from the dataset and using ordinary least square (OLS) to estimate the logarithmic linear form. In contrast, we do not drop the zeros in this paper. We assign the value of one when ODA is equal to zero and take the natural logarithm of ODA commitments. Given the prevalence of zeros and the potential heteroskedasticity of errors, OLS results may exhibit biases and inconsistency. To ensure consistent estimators and address zero-value observations effectively, alternative robust estimators can be used. These alternatives include the Poisson Pseudo-Maximum Likelihood (PPML) estimator, Zero-Inflated Poisson, Heckman selection model, and Probit model (Silva and Tenreyro, 2006; Herrera, 2010; Martin and Hall, 2017). We exploit these alternative estimators to assess the robustness of our estimates.

A statistical consideration arises regarding the potential correlation between disasters and unobserved characteristics of recipients, such as the possibility that poor countries may exhibit both lower resilience to disasters and a higher propensity to receive aid. To address this concern, we incorporate donor-recipient fixed effects (denoted as γ_{dr}) into Equation (1). This adjustment effectively removes time-invariant attributes of recipients and their specific bilateral relationships with donors, allowing us to focus on estimating the impact of disasters by considering only the time variation within donor-recipient pairs. Another issue to contend with is the potential alignment between trends in aid and the frequency of natural disasters. To mitigate this concern, we introduce controls in various forms, including year-fixed effects, donor-year-fixed effects, and time-varying variables such as population and GDP. This approach helps account for any concurrent trends in aid allocation and the occurrence of natural disasters, enabling a proper identification of the effects of disasters on aid distribution. A concluding methodological consideration pertains to inference. Even upon the elimination of donor-recipient and time fixed effects, achieving conditional uncorrelation of error terms within the panel dimensions in Equation (1), a requisite for the consistency of conventional OLS standard errors, remains unlikely. Given the various dimensions available for clustering, we adopt a robust approach by clustering on donor-recipient pairs, which is both the most general and restrictive method (Bertrand et al., 2004).

4. Results

4.1 Does foreign aid increase following natural disasters?

We first test whether the occurrence of a natural disaster leads to an increase in foreign aid commitment in recipient countries. Columns I-III of Table 2 report estimates of Equation (1), in which the occurrence of natural disasters is captured by a dummy as a predictor of bilateral aid commitment. The results suggest a statistically significant and positive direct relationship between aid commitment and natural disasters. This is true whether we control for time-varying influences specific to donors using donor-year fixed effects (Column I), year fixed effects (Column II), or macroeconomic controls (Column III). Using Column III estimates as our benchmark, we interpret results as that the occurrence of a natural disaster increase bilateral aid commitment by about 69 percent.[14] In other words, the average difference in bilateral aid between countries experiencing a natural disaster and those which do not is 69 percent.

When substituting the dummy variable with a measure of damages caused by natural disasters evaluated in US dollars (as shown in Columns IV-VI of Table 2), the results remain statistically significant. Quantitatively, the interpretation of the results using column VI estimates as a benchmark implies that a 1 percent increase in damages caused by natural disaster increase bilateral by about 0.05 percent everything else being equal. The effect of natural disaster on aid commitment appears economically significant. The result should be interpretated as an average response of the main bilateral donors to natural disasters - bilateral aid constitutes 75 percent of ODA. As mentioned earlier we left out the multilateral donor response hence our results should be interpreted as a lower bound of the average overall aid response considering the role that multilateral donors play in disasters.

It should be noted that even though the data on damages is subject to measurement errors and outright missing for many years and types of natural disasters which we bundle together. Despite these limitations, we primarily rely on the measure of damages to capture the timing of natural disasters for our identification and interpretations. The results confirm that the occurrence of a natural disaster causes new bilateral commitment on impact–which is to be expected if the donor's motive is to act as a form of insurance during crisis. More generally, we confirm that aid commitment statistically and economically significantly increases in response to (big) shocks. Yet, the estimates of the average response of aid flows to natural disaster years could mask that other factors interact with shocks to drive donors' response. In other words, there could be a differential effect, depending on donor-recipient and recipient characteristics, which we further explore below. In the following sub-section, we explore further the compositional responses of aid inflows to natural disaster shocks.

4.2 How is the composition of aid evolving following natural disasters?

In this subsection, we test whether the occurrence of a natural disaster affects the composition of foreign aid commitment in recipient countries. Columns I-III of Table 3 report estimates of Equation (1) for humanitarian aid flows. The results suggest a statistically significant and positive direct relationship between humanitarian aid commitment and natural disasters. This is true whether we control for time-varying influences specific to donors using donor-year fixed effects (Column I), year fixed effects (Column II), or macroeconomic controls (Column III). Using Column III estimates as our benchmark, we interpret results as a natural disaster increasing bilateral aid commitment by about 39 percent. In other words, the average difference in humanitarian bilateral aid between countries experiencing a natural disaster and those which do not is 39 percent. When considering non-humanitarian aid as dependent variable (Columns IV-VI), the results become statistically insignificant. The point estimate becomes small, even turning negative.

The results suggest that humanitarian aid flows drive our aggregate aid results presented in the earlier sub-section. It should, however, be noted that the data on humanitarian aid commitment suffers from important limitations. The data is only available from 2005 to 2021. That contrasts with the aggregate aid commitment used in earlier subsection from 1975 to 2021. Hence the results presented in this section should be taken with caution, including the non-result on non-humanitarian aid flows. Notwithstanding the data limitation, we further explore the dynamic of aid and its composition in the robustness section and confirm that humanitarian aid takes precedence over other forms of aid following natural disaster shocks. In the following two sub-sections, we respectively explore whether aid inflows following natural disasters differ, depending on the income level or intensity of damage.

[14] To interpret the quantitative effect of the relevant coefficient associated with a dummy we compute: 100*(exp(coefficient)-1).

4.3 Do poorer countries receive more aid following natural disasters?

In this subsection, we test whether countries with different income levels receive more aid following natural disaster shocks in recipient countries. Columns I-III of Table 4 report estimates of a version of Equation (2) with a series of interaction between natural disasters and income level. The results point to statistically significant and positive interaction terms between various income levels and natural disasters. This is true whether we use different sets of controls (Column I), (Column II), and (Column III).

More importantly, the coefficient associated with the interaction term with the 50th-75th income level is highest across the different specifications. Using Column III estimates as our benchmark, we interpret results as a natural disaster increasing bilateral aid commitment for the 50th-75th income level by about 150 percent. In other words, the average difference in bilateral aid between countries experiencing a natural disaster with 50th-75th income level and those which do not is 150 percent. For comparison, the coefficient associated with the interaction term with lowest income is about 0.5, suggesting the size of the effect is less than half the size of the effect associated with 50th-75th income level. Supplementary Appendix Figure 3 presents graphically the results and confirm the results presented in Table 4 that the peak coefficient is not associated with the lowest income group.

The results suggest that countries with the lowest income do not receive proportionally the most aid following natural disasters. That raises further important issues related to the efficient allocation of aid. Indeed, the stated goal of aid being to serve development goals, one would expect that lowest income countries facing natural disasters receive proportionally more, not less aid.

4.4 Do countries experiencing more damage receive more aid following natural disasters?

In this subsection, we test whether countries with different damage intensity receive more aid following natural disaster shocks in recipient countries. Columns I-III of Table 5 report estimates of a version of Equation (2) with a series of interaction between natural disasters and damage intensity. The results point to statistically significant and positive interaction terms between various damage intensity and natural disasters. This is true whether we use different sets of controls (Column I), (Column II), and (Column III).

More importantly, the coefficient associated with the interaction term with 25h-50th damage per GDP is highest across the different specifications. Using Column III estimates as our benchmark, we interpret results as that the occurrence of a natural disaster increase bilateral aid commitment for 25h-50th damage per GDP by about 180 percent. In other words, the average difference in bilateral aid between countries experiencing a natural disaster with 25h-50th damage per GDP and those which do not is 180 percent. For comparison, the coefficient associated with the interaction term with highest damage is about 0.6 suggesting the size of effect is less than half the size of the effect associated with 25h-50th damage per GDP. Supplementary Appendix Figure 4 presents graphically the results and confirm the results presented in Table 5 that the peak coefficient is not associated with the group of countries facing the biggest damage.

The results suggest that countries with the highest damage do not receive proportionally the most aid following natural disasters. That further raises important issues related to the efficient allocation of aid. Indeed, the stated goal of aid being to serve development goals, one would expect that countries facing the most damage from natural disasters receive proportionally more, not less aid.

4.5 Is foreign aid disbursed faster following natural disasters?

In this sub-section, we test whether recipient countries, which received aid commitments from donor countries, benefit from larger and faster aid disbursements following natural disasters than in the absence of such disasters. To this end, the hypotheses we test concern general models, not whether a response to a particular horizon is statistically different from zero. We test whether the predictive power of committed aid on disbursed aid is higher in the presence of a disaster than in the absence of disaster at a given horizon. Table 6 shows the hypothesis tests for the relevant integrals for different models with different fixed effects and for different horizon levels. For example, we test the null hypothesis that aid disbursement is less than or equal to 0 against our theoretical prediction (that committed aid disbursement is greater in the presence of a disaster shock), namely that it is positive in the first year. Similarly, we test the null hypothesis that the response is less than or equal to 0 against our theoretical prediction that it is positive for horizons 0 to 3.

The results show that in all cases, irrespective of whether we use net or gross disbursement (commitment are gross flows by nature), we cannot reject the null hypothesis in favor of the theoretical prediction at standard levels of statistical significance. For example, the response of aid disbursement is not significantly positive between the year of the disaster and the following year (with a p-value of 0.99), indicating an insignificant anticipation effect for one horizon. The results are similar for periods with two or three-year horizons. The response of aid disbursement is not different from zero in the first three years whether there is a disaster or not.

These results have important implications. The results point to another dimension of inefficiency in the allocation of foreign aid. Given the stated goals, one would expect that aid commitment is more expeditiously disbursed following natural disasters than in the absence of natural disasters. Indeed, countries affected by natural disasters face urgent needs and the speed of disbursement is of the essence in that context. The reason driving that speed (or lack thereof) of disbursement as well as other deficiencies we documented above could be related to several factors including donor-recipient political alignment or recipient absorptive capacity. We turn to explore these mechanisms in the next subsection.

4.6 Is political alignment more potent than absorptive capacity in driving aid inflows following natural disasters?

In this subsection, we test whether donor-recipient political alignment proxied by closedness in UN voting patterns or absorptive capacity proxied by state capacity countries drive aid response following natural disaster shocks in recipient countries. Columns I-III of Table 7 report estimates for a regression using as dependent aid commitment over several horizons following natural disasters. The regression uses a version of Equation (2) with a series of interaction between natural disasters, political alignment, state capacity as well as double interaction. The results point to statistically significant and positive interaction terms between natural disasters, political alignment, and state capacity. This is true at different horizons following natural disasters (Columns I-IV).

More importantly, the coefficients associated with individual effect of natural disasters, and the relevant interaction terms associated with natural disasters suggest at low/medium level of state capacity and high level of political alignment the latter dominate. Using Column III in Table 7 estimates as our benchmark, we interpret results as political alignment and state capacity interacting with the occurrence of a natural disaster to drive bilateral aid commitment three years following the disasters. Both coefficients associated with the simple interactions between natural disaster and respectively political alignment and state capacity are positive and large. The coefficient associated with state capacity is slightly larger. The double interaction term including the interaction with political alignment and state capacity is large and negative indicating it has little quantitative significance. Political alignment and state capacity seem to play out independently.

These results suggest that countries with modest levels of state capacity that correspond to low capacity of absorption will receive much less aid. following natural disasters. That raises important issues related to the efficient allocation of aid following natural disasters. Indeed, the stated goal of aid being to serve development goals, one would expect that countries with low state capacity facing natural disasters receive proportionally more, not less aid to reinforce their resilience. Critics could argue that if a would-be recipient facing a natural disaster has low state capacity a donor may hesitate to provide aid for fear that it would be wasted. Yet, in the example of Haiti, donors circumvented the government to deliver aid which arguably exhibited low state capacity. It is precisely when countries have low state capacity that they are the most vulnerable to shocks such as natural disasters (IMF, 2019). Besides humanitarian aid, donors should focus on aid that help build that resilience.

5. Extensions and Robustness Checks

In this section, we explore a variety of robustness checks and extensions. First, we test whether our main results are robust by using different estimators to account for the presence of too many zeros. Table 8 in Supplementary Appendix presents the results from the estimation of Equation (1) using OLS which is our benchmark as well as alternative estimators namely Poisson Pseudo-Maximum Likelihood, Zero-Inflated Poisson, Heckman selection model, and Probit model. The coefficient associated with Columns (I-V) suggests that the coefficients associated with natural disaster capturing the average effect of damage on bilateral aid is statistically significant across the different estimators. Our main results are robust to using different estimators accounting for the presence of too many zero observations.

We then test whether our main results on the effect of natural disaster damages on bilateral aid is robust to the missing information on damage. Table 9 in Supplementary Appendix presents the results from the estimation of Equation (1) augmented with a dummy accounting for the missing information on damage. The coefficient associated with Columns (I-III in Table 9) suggests that the coefficient associated with natural disaster damage capture the average effect of damage on bilateral aid is statistically significant across the different specifications. Quantitatively, the effect is similar to the one presented in the main result section in Table 2. Further, the coefficient associated with the dummy variable capturing the missing information is also statistically significant, indicating that the missing information does carry meaningful variation on natural disaster shocks. Notwithstanding the robustness of our results accounting for missing information, the significance of the dummy association with missing values for damage vindicate our choice in relying on the dummy variable to identify the effect of natural disaster shocks on bilateral aid.

We then turn to Table 10 in Supplementary Appendix where we explore the effects of all natural disasters on foreign aid. Columns (I) to (III) present the results of estimation of Equation (1) using dummy variables to capture the timing of natural disasters using different sets of controls. Coefficients associated with all disasters are almost always statistically significant but vary in size across different specifications. Using Column (III) as our benchmark, we find that the bigger coefficients in size (and statistically significant) are associated with select natural disasters namely extreme temperatures, wildfire, landslide (wet) and infestation. When using damage as proxy for natural disasters, results for different specifications presented in Columns (IV) to (VI) appear less robust albeit the pattern of statistical significance resemble the one for Columns (I) to (III). Quantitatively, we found, using Column (VIII) as our benchmark, that the bigger statistically significant coefficients are associated with extreme temperatures, flood, and landslide (dry) and wildfire. These results confirm the heterogeneity along disaster type in the response of bilateral aid.

To explore the dynamic of the effect of natural disaster on the volume and the composition of aid, we generated impulse response function using the so-called local-projection method (Jorda`, 2005). Figure 5 in the Supplementary Appendix presents the impulse response function for aggregate aid following natural disasters. Figure 5 shows a peak on impact and a slow decline in the response function which becomes statistically insignificant after five years of the occurrence of the disaster. Figures 6 and 7 present the impulse response for respectively humanitarian and non-humanitarian aid. The results point to humanitarian aid peaking on impact was non humanitarian peak after the impact. The response of non-humanitarian aid is more muted as shown by the differences in size of peak effects presented in the last two impulse responses. The results confirm our earlier and main results presented in Table 3 of the main paper that humanitarian aid drive the effect of aid following natural disasters. In addition, we use an alternative estimation method to account for the so-called staggered treatment concerns. To do so, we apply the local projection difference-in-difference (LP-DiD) method proposed by Dube et al (2023). Our results are y robust especially when we consider that once a unit is treated, the unit remains treated (see Figure 8).

We explore whether aid in the form of grants or loans differ in their responses to natural disasters. Tables 11 and 12 in supplementary appendix present the results of the estimation of Equation (1) using grants and loans, respectively. Results point to statistical significance across the board for both grants and loans except for Column (III) of loans. Quantitatively, the size of the coefficient including when using damage information suggests that the response of grant is overwhelmingly higher than loans in response to natural disasters. These results conform with the earlier results that humanitarian aid dominate. That said, the overall size of the effect is relatively small in comparison to the damage caused by natural disasters.

Finally, we explore the robustness of our results across different samples, including alternative periods such as 1990-2021 and 2000-2021 instead of 1975-2021. Our findings consistently hold across these various sample periods (see Tables 13 and 14). Additionally, when analyzing samples that include only small island countries or exclude them entirely, our results remain robust, with the effects being more pronounced for non-island countries (see Tables 15 and 16). Because natural disasters that immediately follow a previous natural disaster could be seen as predictable, we check whether our main results are robust to removing the immediately following natural disasters (see Tables 17 and 18). We also selectively use natural disasters that occurred when no natural disasters happened in the past three years (see Tables 19 and 20). Our results remain largely robust to these alterations.

6. Conclusion

In this paper, we explored the effect of shocks on the responsiveness and allocation of (bilateral) aid using disasters as natural experiments. We found that aid commitment statistically and economically significantly increases following natural disasters, and that humanitarian aid precedes structural aid. However, we found that the poorest countries or countries faced with most damaging natural disasters do not receive the most aid. That pattern of allocation appears inefficient because investing aid in the latter countries could deliver the biggest "bang for the buck". We also did not find evidence that foreign aid commitment disburses faster following natural disasters. Further explorations into the mechanisms driving aid in disaster countries pointed to the importance of low state capacity and political alignment with (major) donors in recipient countries.

The increase frequency and intensity of natural disasters caused by climate change implies that the composition of aid is shifting toward a more "reactive" form. In turn, less structural, developmental aid means an increase in the vulnerability of natural disaster-prone countries necessitating more reactive aid. The aid industry could become unsustainable. Low-income countries often with low state capacity are the most prone to the effect of natural disasters, yet we show they do not get the most aid in response. Considerations of political alignment between donor and recipient are coming in the way of a more efficient allocation. Beyond aid, low-income countries also typically have limited access to capital and insurance markets. Investing in the resilience of low countries including in state capacity could not only facilitate the disbursement of aid inflows in recipient countries but also facilitate access to capital and insurance markets. A promising direction for future research is to explore the importance of state capacity as a mechanism for "insurance" at the macroeconomic level in the face of natural disasters.

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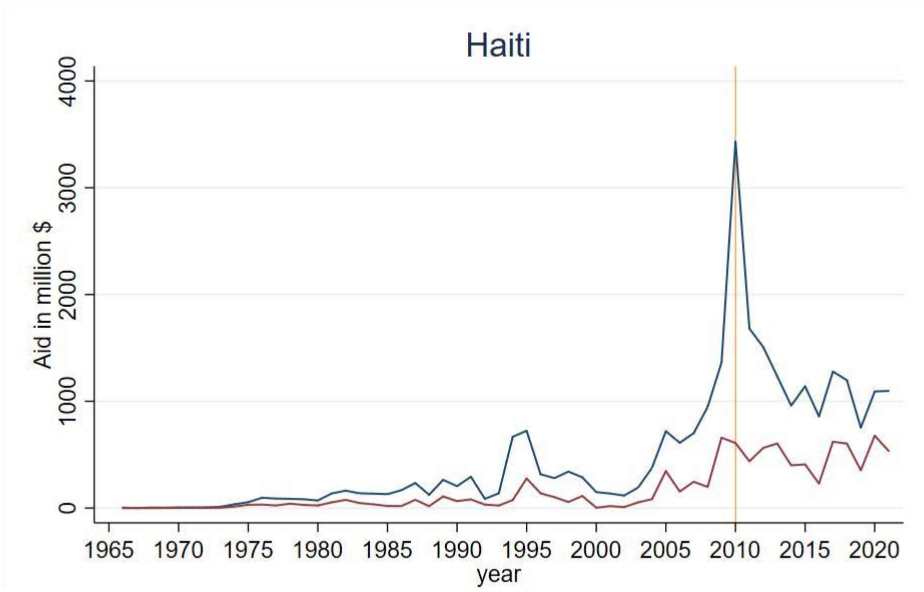
Appendices

Figure 1: Evolution of bilateral and multilateral aid commitments in Haiti



Notes: The Figure shows the evolution of bilateral aid commitments (in blue) and multilateral aid commitments (red) for Haiti. The official development assistance (ODA) data are obtained from OECD, Development Assistance Committee (DAC).

Figure 2: Evolution of number of natural disasters

Notes: The figure shows the evolution of total number of natural disasters, obtained from EM-DAT database.

Figure 3: Effect of natural disasters in recipient countries with interaction with income group levels on foreign aid

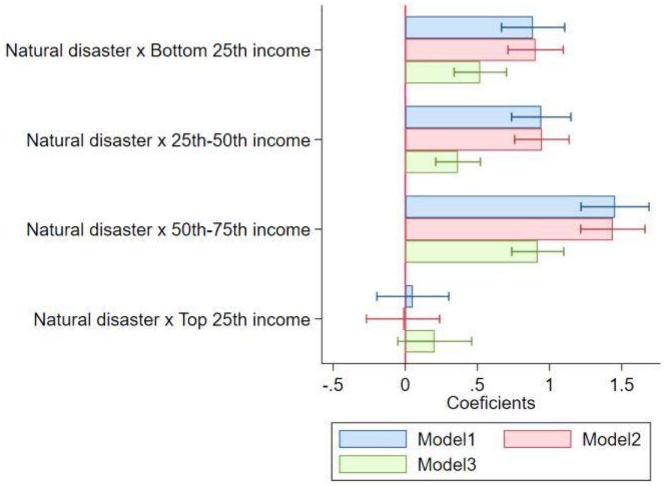


Figure 4: Effect of natural disasters in recipient countries with interaction with damage levels on foreign aid

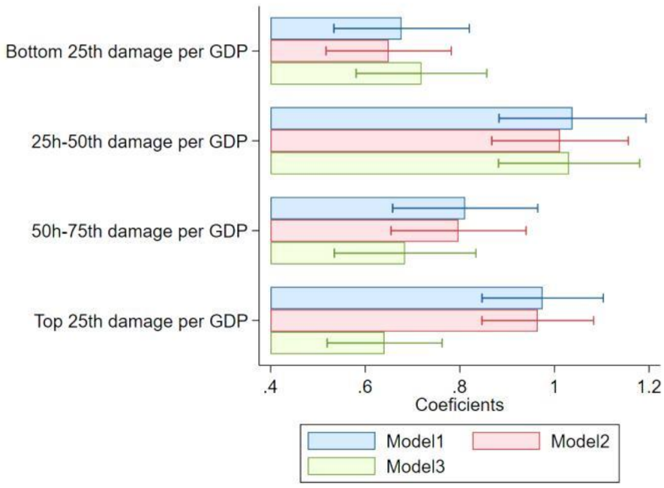
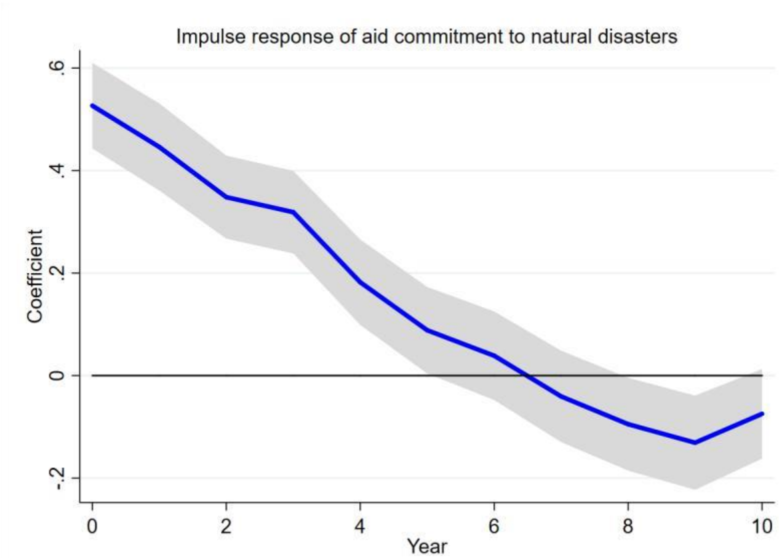
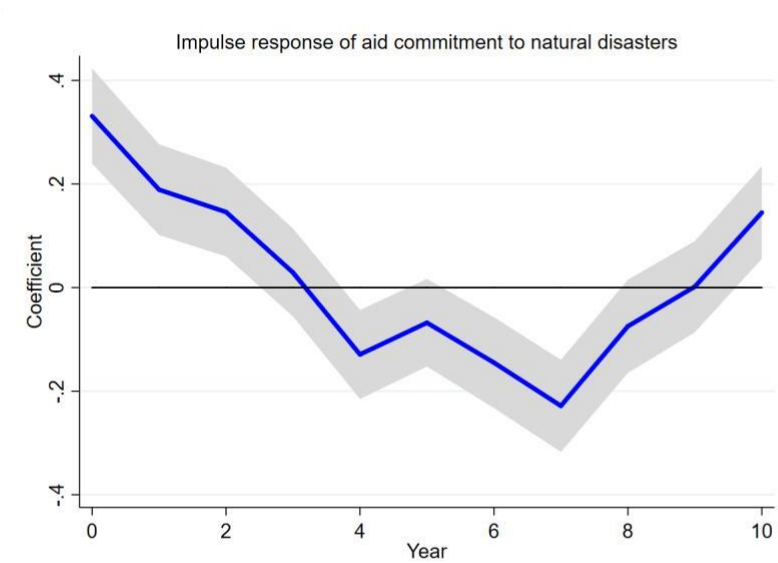


Figure 5: Dynamic response of bilateral aid commitment to natural disasters



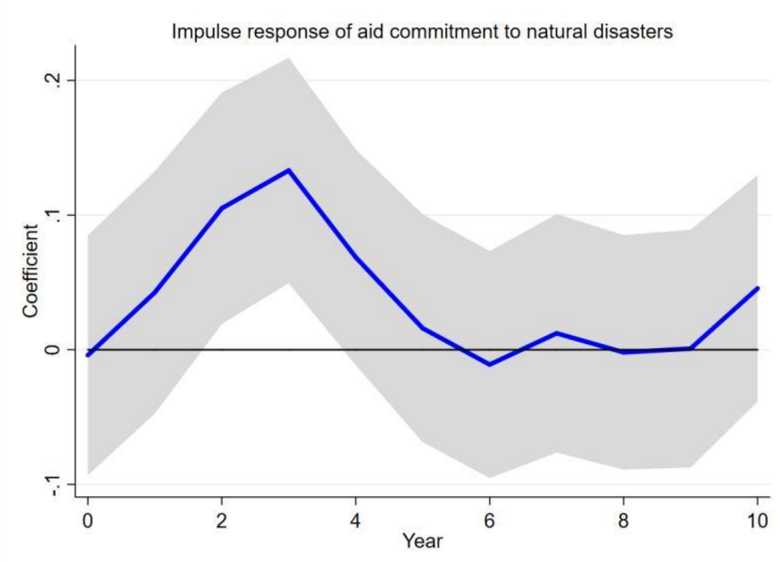
Notes: The figure presents the impulse response of an aid commitment with natural disaster dummy shock. The blue line indicates point estimates, and gray areas are 90%. The vertical axis shows percentage changes.

Figure 6: Dynamic response of bilateral humanitarian aid to natural disasters



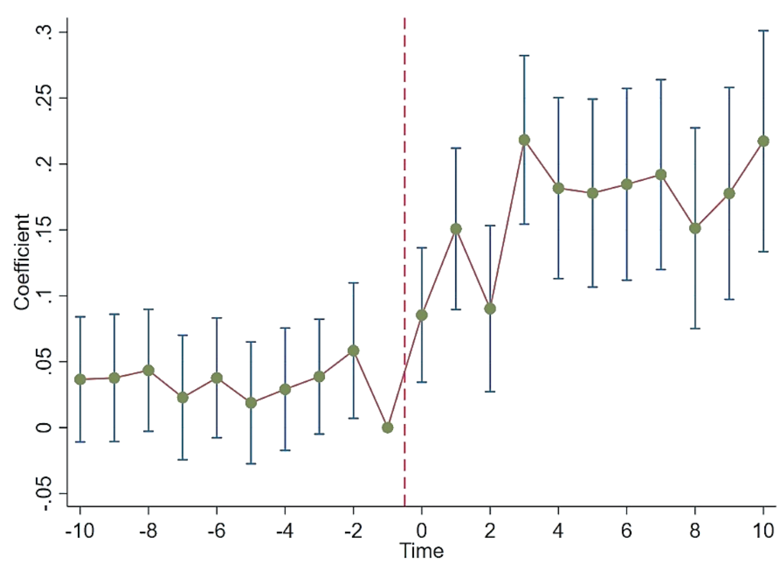
Notes: The figure presents the impulse response of a humanitarian aid commitment with natural disaster dummy shock. The blue line indicates point estimates, and gray areas are 90%. The vertical axis shows percentage changes.

Figure 7: Dynamic response of bilateral non-humanitarian aid to natural disasters



Notes: The figure presents the impulse response of a non-humanitarian aid commitment with natural disaster dummy shock. The blue line indicates point estimates, and gray areas are 90%. The vertical axis shows percentage changes.

Figure 8: Dynamic response of bilateral aid to natural disasters using local projection difference-in-difference method



Notes: The figure presents the event study of bilateral aid commitment with natural disaster dummy shock using local projection difference-in-difference (LP-DiD) as in Dube et al (2023). We rely here on the treatment absorbing assumption.

Table 1: Descriptive Statistics

Variable	N	Mean	SD
Donor/Recipient/Year Level			
ODA	151,076	25.76	402.79
Recipient/Year Level			
Natural disaster	8,854	0.45	0.50
Political alignment	4,336	0.53	0.13
State capacity	6,521	0.56	0.16
GDP	7,109	89,848	539,508
Population	8,351	28.67	122.37
Donor/Year Level			
GDP (Donor)	906	1,472,285	2,841,205
Population (Donor)	911	70.67	189.53

Notes: Official Development Assistance (ODA) is total aid commitments in millions of US dollars. Natural disaster is a dummy variable for recipient countries that have experienced natural disasters. Political alignment is the average probability of agreement between the G7 donor and recipient countries when voting at the United Nations. GDP is expressed in millions of US dollars. Population is expressed in millions of inhabitants. State capacity is an index of state capacity ranging from 0 (low capacity) to 1 (high capacity).

Table 2: Effect of natural disasters in recipient countries on foreign aid

	(I)	(II)	(III)	(IV)	(V)	(VI)
		Bilateral aid			Bilateral aid	
Natural disaster (dummy)	0.952***	0.939***	0.527***			
	(0.051)	(0.048)	(0.043)			
Damage				0.048***	0.047***	0.045***
				(0.003)	(0.003)	(0.003)
Recipient GDP			-1.310***			-1.329***
			(0.083)			(0.083)
Donor GDP			2.865***			2.884***
			(0.117)			(0.116)
Recipient population			1.319***			1.414***
			(0.300)			(0.300)
Donor population			-1.245***			-1.244***
			(0.156)			(0.155)
Observations	151,076	151,076	126,810	151,076	151,076	126,810
R-squared	0.593	0.649	0.611	0.592	0.648	0.611
Fixed effects	DR-Y	DR-DY	DR	DR-Y	DR-DY	DR

Notes: The table shows the results of regressions of different natural disasters in the recipient country on bilateral aid committed by the donor country to the recipient country. Each column reports a separate regression. The dependent variable in all columns is logarithm of bilateral ODA. All control variables are in logarithmic form. Natural disaster (dummy) is a dummy variable which takes the value 1 if the recipient country has suffered natural disasters. Damage is the logarithm of overall damage value in US dollars at the time of the natural disasters in the recipient country. Fixed effects are denoted DR for donor-recipient pair, Y for year, and DY for donor-year pair. The number of observations in columns (III) and (VI) are smaller since these regressions include macroeconomic indicators that are not available for all countries and all years (see Appendix for details). Constant terms are included in all regressions and not reported to save space. Standard errors in parentheses are clustered at donor-recipient pair level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Effect of natural disasters in recipient countries on the composition of foreign aid

	(I)	(II)	(III)	(IV)	(V)	(VI)
		Humanitarian aid			Aid excl. humanitarian	
Natural disaster (dummy)	0.373***	0.369***	0.331***	0.049	0.049	-0.004
	(0.047)	(0.046)	(0.047)	(0.047)	(0.045)	(0.045)
Recipient GDP			-1.445***			-0.619***
			(0.150)			(0.097)
Donor GDP			1.623***			2.416***
			(0.154)			(0.196)
Recipient population			2.057***			-1.941***
			(0.485)			(0.362)
Donor population			-0.324			3.664***
			(0.247)			(0.372)
Observations	55,566	55,566	52,791	55,566	55,566	52,791
R-squared	0.604	0.629	0.608	0.788	0.807	0.794
Fixed effects	DR-Y	DR-DY	DR	DR-Y	DR-DY	DR

Notes: The table shows the results of regressions of natural disasters in the recipient country on bilateral humanitarian aid and bilateral aid excluding humanitarian aid over the periods 2005-2021. Each column reports a separate regression. The dependent variable in columns (I) - (III) is the logarithm of bilateral humanitarian aid, and in columns (IV) - (VI) is the logarithm of bilateral aid excluding humanitarian aid. All control variables are in logarithmic form. Natural disaster (dummy) is a dummy variable which takes the value 1 if the recipient country has suffered natural disasters. Fixed effects are denoted DR for donor-recipient pair, Y for year, and DY for donor-year pair. The number of observations in columns and (VI) are smaller since these regressions include macroeconomic indicators that are not available for all countries and all years (see appendix for details). Constant terms are included in all regressions and not reported to save space. Standard errors in parentheses are clustered at donor-recipient pair level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Effect of natural disasters in recipient countries with interaction with income group level on foreign aid

	(I)	(II)	(III)
		Bilateral aid	
Natural disaster x Bottom 25th income	0.886***	0.903***	0.519***
	(0.112)	(0.098)	(0.092)
Natural disaster x 25th-50th income	0.943***	0.947***	0.365***
	(0.105)	(0.096)	(0.079)
Natural disaster x 50th-75th income	1.454***	1.439***	0.918***
	(0.120)	(0.114)	(0.092)
Natural disaster x Top 25th income	0.052	-0.016	0.203
	(0.127)	(0.129)	(0.131)
Recipient GDP			-1.309***
			(0.084)
Donor GDP			2.862***
			(0.117)
Recipient population			1.314***
			(0.301)
Donor population			-1.243***
			(0.155)
Observations	145,946	145,946	126,810
R-squared	0.594	0.651	0.611
Fixed effects	DR-Y	DR-DY	DR

Notes: The table shows the results of regressions of different natural disasters in the recipient country on bilateral aid committed by the donor country to the recipient country. Each column reports a separate regression. The dependent variable in all columns is the logarithm of bilateral ODA. All control variables are in logarithmic form. Natural disaster is a dummy variable which takes the value 1 if the recipient country has suffered natural disasters. Bottom 25th income is a dummy variable that takes the value 1 if the recipient country is in the bottom 25th income countries. 25th-50th income is a dummy variable that takes the value 1 if the recipient country is in the between 25th income countries and 50th countries. 50th-75th income is a dummy variable that takes the value 1 if the recipient country is in the between 50th income countries and 75th countries. Top 25th income is a dummy variable that takes the value 1 if the recipient country is in the top 25th income countries. Fixed effects are denoted DR for donor-recipient pair, Y for year, and DY for donor-year pair. The number of observations in column (III) is smaller since these regressions include macroeconomic indicators that are not available for all countries and all years (see Appendix for details). Constant terms are included in all regressions and not reported to save space. Standard errors in parentheses are clustered at donor-recipient pair level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Effect of natural disasters in recipient countries with interaction with damage levels on foreign aid

	(I)	(II)	(III)
		Bilateral aid	
Bottom 25th damage per GDP	0.677***	0.650***	0.719***
	(0.073)	(0.068)	(0.070)
25h-50th damage per GDP	1.038***	1.012***	1.031***
	(0.079)	(0.074)	(0.076)
50h-75th damage per GDP	0.811***	0.797***	0.684***
	(0.078)	(0.073)	(0.076)
Top 25th damage per GDP	0.975***	0.965***	0.641***
	(0.065)	(0.060)	(0.062)
Recipient GDP			-1.324***
			(0.083)
Donor GDP			2.888***
			(0.116)
Recipient population			1.397***
			(0.300)
Donor population			-1.246***
			(0.155)
Observations	151,076	151,076	126,810
R-squared	0.592	0.648	0.611
Fixed effects	DR-Y	DR-DY	DR

Notes: Note: The table shows the results of regressions of different natural disasters in the recipient country on bilateral aid committed by the donor country to the recipient country. Each column reports a separate regression. The dependent variable in all columns is the logarithm of bilateral ODA. All control variables are in logarithmic form. Bottom 25th damage per GDP is a dummy variable that takes the value 1 if the recipient country is in the bottom 25th damage per GDP countries. 25th-50th damage per GDP is a dummy variable that takes the value 1 if the recipient country is in the between 25th damage per GDP and 50th damage per GDP countries. 50th-75th damage per GDP is a dummy variable that takes the value 1 if the recipient country is in the between 50th countries and 75th countries. Top 25th damage per GDP is a dummy variable that takes the value 1 if the recipient country is in the top 25th damage per GDP countries. Fixed effects are denoted DR for donor-recipient pair, Y for year, and DY for donor-year pair. The number of observations in column (III) is smaller since these regressions include macroeconomic indicators that are not available for all countries and all years (see Appendix for details). Constant terms are included in all regressions and not reported to save space. Standard errors in parentheses are clustered at donor-recipient pair level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Test of speed of disbursement of commitment following natural disasters

Net disbursement

	Theoretical prediction for alternative hypothesis H1	Hypothesis test	P-value
Model 1 (with DR-Y FE)	More disbursement at horizon 1	$H0 : \sum_{h=1}^{1} \beta h - \theta h \leq 0$	1.0
Model 2 (with DR-DY FE)		vs	.996
Model 3 (with DR FE/GDP)		$H1 : \sum_{h=1}^{1} \beta h - \theta h > 0$	.999
Model 1 (with DR-Y FE)	More disbursement at horizon 2	$H0 : \sum_{h=1}^{2} \beta h - \theta h \leq 0$	1.0
Model 2 (with DR-DY FE)		vs	.999
Model 3 (with DR FE/GDP)		$H0 : \sum_{h=1}^{2} \beta h - \theta h > 0$	.999
Model 1 (with DR-Y FE)	More disbursement at horizon 3	$H0 : \sum_{h=1}^{3} \beta h - \theta h \leq 0$	1.0
Model 2 (with DR-DY FE)		vs	.999
Model 3 (with DR FE/GDP)		$H0 : \sum_{h=1}^{3} \beta h - \theta h > 0$	.999

Gross disbursement

	Theoretical prediction for alternative hypothesis H1	Hypothesis test	P-value
Model 1 (with DR-Y FE)	More disbursement at horizon 1	$H0 : \sum_{h=1}^{1} \beta h - \theta h \leq 0$	1.0
Model 2 (with DR-DY FE)		vs	1.0
Model 3 (with DR FE/GDP)		$H0 : \sum_{h=1}^{1} \beta h - \theta h > 0$	1.0
Model 1 (with DR-Y FE)	More disbursement at horizon 2	$H0 : \sum_{h=1}^{2} \beta h - \theta h \leq 0$	1.0
Model 2 (with DR-DY FE)		vs	1.0
Model 3 (with DR FE/GDP)		$H0 : \sum_{h=1}^{2} \beta h - \theta h > 0$	1.0
Model 1 (with DR-Y FE)	More disbursement at horizon 3	$H0 : \sum_{h=1}^{3} \beta h - \theta h \leq 0$	1.0
Model 2 (with DR-DY FE)		vs	1.0
Model 3 (with DR FE/GDP)		$H0 : \sum_{h=1}^{2} \beta h - \theta h > 0$	1.0

Note:

Model 1 (with DR-Y Fixed Effects): $Disbursement_{dr,t} = \sum_{h=1}^{H} \beta_h Commitment_{dr,t-h} * NoDisaster_{r,h} + \sum_{h=1}^{H} \theta_h Commitment_{dr,t-h} * Disaster_{r,h} + \gamma_{dr} + \gamma_t + \mathcal{E}_{dr,t}$

Model 2 (with DR-DY Fixed Effects): $Disbursement_{dr,t} = \sum_{h=1}^{H} \beta_h Commitment_{dr,t-h} * NoDisaster_{r,h} + \sum_{h=1}^{H} \theta_h Commitment_{dr,t-h} * Disaster_{r,h} + \gamma_{dr} + \gamma_{dt} + \mathcal{E}_{dr,t}$

Model 3 (with DR Fixed Effect and GDP and Population): $Disbursement_{dr,t} = \sum_{h=1}^{H} \beta_h Commitment_{dr,t-h} * NoDisaster_{r,h} + \sum_{h=1}^{H} \theta_h Commitment_{dr,t-h} * Disaster_{r,h} + \gamma_{dr} + \delta * GDP/Population + \mathcal{E}_{dr,t}$

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