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Natural Disasters and Foreign Aid Allocation:
How Much, How Quickly, and to Whom?

Rabah Arezki, Youssouf Camara,
Patrick Imam, Roland Kangni Kpodar

Rabah Arezki, FERDI, Université Clermont Auvergne, CNRS, IRD, CERDI, F-63000, Clermont-Ferrand, France, and Harvard Kennedy School of Government.

Youssouf Camara, McGill University.

Patrick Imam, International Monetary Fund (IMF).

Roland Kangni Kpodar, FERDI and International Monetary Fund (IMF).

Abstract

Natural disasters provide quasi-experimental variation to study how foreign aid responds to shocks. Using data for 20 bilateral donors for the period going from 1995 to 2021 and a local-projection difference-in-differences design, we estimate the dynamic effects of disasters on aid commitments. Foreign aid rises significantly in the aftermath of shocks, but the response is short-lived and disproportionately benefits middle-income countries. Humanitarian aid reacts quickly, while development aid adjusts more slowly. The findings reveal persistent inequities in global disaster relief.

Keywords: Natural Disasters, Quai-experiment, Aid Allocation, Humanitarian Aid.

JEL Codes: E00, F3, O1, O2.

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1. Introduction

Foreign aid is designed to promote economic development and reduce vulnerability in recipient countries, yet the volume, timeliness and composition of aid allocation has been subject to intense debate.[1] Natural disasters provide a powerful lens through which to study the question of aid allocation. The timing of natural disasters is largely exogenous, creating quasi-experimental conditions that reveal the attributes of the dynamic response of foreign aid. Disasters generate sharp, visible humanitarian needs, but they also test whether donors respond where the need is greatest. In the present paper, we exploit this setting to examine how bilateral donors adjust their aid in the aftermath of major disasters, how much they give, how quickly, and to whom.

While the timing of natural disasters is arguably exogenous, the extent of damage, stemming from the combination of intensity of the shocks and the exposure of the country facing the shock cannot be argued to be fully 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 uses primarily the timing of natural disasters for identification purposes. In turn, that allows for the identification of the causal relationship between the occurrence of natural disasters and the allocation of aid.

Our study is linked to the literature seeking to exploit quasi-randomness to study aid as surveyed by Dreher et al. (2024). 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). More closely related to our paper is Becerra et al. (2014) who provide early evidence related to the response of aid flow following natural disasters. Using an event study for the period running between 1970 and 2008, the authors find that while aid increases, the typical surge is small in relation to the size of the affected economies. In this paper, we use state-of-the art techniques to explore the effects of natural disasters on foreign aid exposing the variability of effects across different disaster types.

[1] The literature on aid allocation is abundant. Maizels and Nissanke (1984), Dollar and Alesina (2000), Alesina and Weder (2002) and Knack (2001) are amongst the early contribution to the strand of literature on aid allocation.

Our paper also complements the strand of literature exploring the dynamics and composition of aid allocation. That strand of literature is organized along two dimensions namely on the composition of aid allocation (development aid vs. humanitarian assistance) and the level of the allocation (country level vs. subnational level). On the former, Fuchs and Siewers (2025) show that donor countries take faster aid decisions if they have stronger strategic interests at stake. On the latter, Bommer, Dreher and Perez-Alvarez (2022) study humanitarian aid allocation at the subnational level. The authors provide evidence of the role of regional favoritism in the allocation of international disaster relief.[2] In this paper, we contribute to this literature by highlighting systematically that foreign aid does not flow to most affected and poorest countries following natural disasters.

The main contribution of this paper is to offer coherent and comprehensive insights into the effect of natural disasters on foreign aid. Our paper contrasts with the more fragmented set of results one can gather from existing work. Specifically, our central question is straightforward: how do bilateral donors adjust aid commitments following natural disasters, and who benefits most from these changes in commitments?[3] To answer it, we compile a new panel dataset covering 20 bilateral donors, including both Development Assistance Committee (DAC) members and emerging partners such as China, and 189 recipients over 1995–2021. Using a local-projection difference-in-differences (LP-DiD) framework, we estimate the dynamic effects of disasters on aid commitments, distinguishing between humanitarian and development flows. This approach captures both the immediate surge in emergency aid and the medium-term evolution of broader support, while accommodating staggered treatment timing and heterogeneous exposure across countries.

The 2010 Haiti earthquake illustrates the importance of studying systematically the response of foreign aid to natural disasters. The Haiti example reveals that disasters can shift both the volume and composition of aid toward recipient countries affected by natural disasters. Figure 1 in the Appendix presents the evolution of aid commitments to Haiti from both bilateral and multilateral

[2] Fink and Radaelli (2011) and Annen and Strickland (2017) both examine the political economy of humanitarian aid allocation.

[3] Data limitations linked to reporting on project amendments and donor reprogramming prevent us from analysis the reallocation of foreign aid. We thus interpret our results as "changes" in aid commitments at the onset of the disasters.

sources. It illustrates 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. 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.[4] This 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?

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 follow the approach of 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 identifying the effect of natural disasters on foreign aid.

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 official development assistance (ODA). Data on ODA flows are provided by the 29 Organization

[4] 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.

of Economic Cooperation and Development (OECD) members of the DAC.[5] We exclusively use bilateral aid, as opposed to multilateral aid, which accounts for about 75 percent of overall aid globally according to the OECD. In this paper, we leave out from our analysis multilateral aid which is pooled from multiple countries.

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.

Our results are also related to the strand of literature 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.[6] 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 including of different types (see Figure 2 in the Appendix). 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.

[5] 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. While 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.

[6] See 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.

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. Table 1 in the Appendix presents a summary of descriptive statistics.

Foreign aid is our main dependent variable. Foreign aid data known as ODA covers the period going from 1975 to 2021. ODA is retrieved from OECD's DAC database. We exclusively 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. 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 (2023)'s Global Chinese Development Finance.[7] We include China and other non-DAC donors for comparison only, to assess whether their post-disaster responses differ systematically from those of DAC donors, rather than to make them the central focus of the analysis. 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

[7] We use version 3.0 of AidData retrieved from https://www.aiddata.org/data/aiddatas-global-chinese-development-finance-dataset-version-3-0.

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 and in-kind contributions (or pledges) from China over the specified timeframe. The dataset's granularity and scope offer a unique lens into the landscape of Chinese development finance.

Throughout the analysis, we focus on *aid allocation*, measured as total bilateral commitments from DAC and non-DAC donors. These are pledges of support rather than realized disbursements or the specific *implementation channels* through which assistance is delivered. This distinction matters because humanitarian commitments may include multi-year programs or projects planned before the disaster, and donors often rely on NGOs or multilateral agencies to deliver aid in low-capacity environments. Our results should therefore be interpreted as evidence on how donors adjust the *volume and type* of aid they commit after disasters, rather than on how these resources are ultimately channeled on the ground.

Natural disasters are our main explanatory variable. Data for natural disasters are from the Emergency Events Database (EM-DAT) by the *Centre de recherche sur l'épidémiologie des catastrophes (CRED)*.[8] 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.

[8] Data are drawn from the Emergency Events Database (EM-DAT, 2022).

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.

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:

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

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.

Bilateral aid flows between a specific donor and recipient over time involves 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 concluding methodological consideration pertains to inference. Even upon the elimination of donor-recipient and time fixed effects, ensuring that error terms are conditionally uncorrelated within panels 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?

Our empirical analysis centers on three main questions. First, how do total bilateral aid commitments respond dynamically to natural disasters? Second, does the composition of aid. between humanitarian and other forms, shift following a shock? Third, which country's characteristics shape the magnitude of these responses? The remaining tests, including robustness checks, alternative samples, and extensions by disaster type, serve to confirm the stability of these core findings rather than to introduce additional hypotheses.

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 in Appendix 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 increases bilateral aid commitment by about 69 percent.[9] 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 damage 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 damage caused by natural disasters increased bilateral aid by about 0.05 percent everything else being equal. The effect of natural disaster on aid commitment appears economically significant. That said, that increase in aid commitment provided it is disbursed is insufficient to cover the needs, especially in low-income countries which have no alternative of financing. The results should be interpreted 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 disasters. Yet, the estimates of the average response of aid flows to natural disaster years could mask that heterogeneity along different types of disasters. We thus turn to Table 3 in Appendix where we explore the effects of different types of 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

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

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 resembles 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 suggest an underlying mechanism that disasters which create a sense of urgency because of human casualties and physical damage ignite the most significant changes in aid commitments.
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 4 in Appendix 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.

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 5 in Appendix report estimates of a version of Equation (2) with a series of interactions 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. Figure 3 in the Appendix reports the local-projection impulse responses with 90 percent confidence intervals (shaded areas), confirming that the post-disaster increase in aid is statistically significant and short-lived. Figure 3 presents graphically the results and confirms the results presented in Table 5 in the Appendix 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 will 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 6 in Appendix report estimates of a version of Equation (2) with a series of interactions 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 increases 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 effect associated with 25h-50th damage per GDP. Appendix Figure 4 presents graphically the results and confirms the results presented in Table 6 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.[10] To this end, the hypotheses we test concern general models, not

[10] The test is using aggregate and not project level data. While the OECD's Development Assistance Committee (DAC) dataset we use in this paper is not broken down at the project level, the aggregate test we perform provide evidence that aid flow does not disburse faster in the presence of disasters—compared to the rest of the time when there is no disaster. We leave for further research the project level analysis—perhaps using a more restricted set of donor data where the breakdown might be available.

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 7 in Appendix 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.

5. Extensions and Robustness Checks

In this section, we explore a variety of robustness checks and extensions. The following extensions and robustness tests validate the main results and explore additional dimensions, including subperiod stability, alternative intensity measures, and heterogeneity amongst donors. 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 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 disasters 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 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 vindicates our choice in relying on the dummy variable to identify the effect of natural disaster shocks on bilateral aid.

To explore the dynamics of the effect of natural disasters 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 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 in the Appendix 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 4 of the main paper that humanitarian aid drives 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 robust especially when we consider that once a unit is treated, the unit remains treated (see Figure 8 in the Appendix).

We explore whether aid in the form of grants or loans differ in their responses to natural disasters. Tables 10 and 11 in 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.

We now turn to exploring whether there is potential heterogeneity of our main results vis-à-vis donors. The findings presented in Table 12 in the Appendix indicate that our main results showing that foreign aid increase significantly following natural disasters are neither driven by China, nor by Arab donors. Indeed, Table 12 shows that when estimating the relationship between foreign aid and natural disasters for samples restricted to respectively Arab donors and China the results are positive but not robust in terms of significance across specifications. These results vindicate our choice of focusing on the aggregate response of aid following natural disasters rather than on the heterogeneity amongst donors.

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 in the Appendix). 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 in the Appendix). 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 18 and 19 in the Appendix).[11] We also selectively use natural disasters that occurred when no natural disasters happened in the past three years (see Tables 20 and 21 in the Appendix). Our results remain largely robust to these alterations.

[11] In Table 17, we show results on the effect of future and past natural disasters. The correlation between future disasters and current commitment is significantly positive although the coefficient drops significantly in size as the number of leads increases. While puzzling these results may simply relate to the bunching of natural disasters over time and space. As such, these specific results cannot be interpreted as deriving from a valid placebo test. Subsequently, we address the potential bias emerging from bunching of natural disasters.

6. Conclusion

This paper examined how bilateral donors adjust aid commitments after natural disasters, using the exogenous timing of shocks as a natural experiment within a local-projection difference-in-differences framework. We find that total aid commitments rise significantly following disasters, with humanitarian assistance responding immediately and development aid adjusting more gradually. Yet the pattern of response is uneven. The poorest countries and those experiencing the most damaging disasters do not receive the largest increases in aid, despite being the places where additional support could deliver the greatest development gains. We also find no systematic evidence that disbursements accelerate after disasters. Beyond issues of disbursement, it is important to distinguish between allocation (how much aid is given) and implementation channels (to whom it is transferred). Further research should explore these issues of implementation channels.

These findings point to an aid system that is reactive but selective. Donors do respond to acute shocks, but strategic and institutional considerations play a substantial role in determining the scale and direction of support. As climate change increases the frequency and severity of natural disasters, the aid portfolio appears to be shifting toward short-term humanitarian relief. While lifesaving, this reactive tilt risks crowding out long-term, developmental assistance, leaving vulnerable countries even more exposed in the future. Low-income countries, often with weak state capacity, face a double disadvantage. They are most vulnerable to shocks but do not receive proportionately larger post-disaster increases in aid.

These dynamics have broader implications for resilience. Low-capacity countries typically have limited access to capital and insurance markets, restricting their ability to self-insure against disasters. Investing in state capacity could therefore yield a double dividend. It would improve the ability of governments to absorb and deploy aid effectively, and it could expand their access to external financing and disaster-risk instruments. Donors, for their part, may need to complement emergency relief with more predictable structural support aimed at preparedness, infrastructure, and institutional capability. A more balanced allocation between reactive humanitarian aid and forward-looking resilience building is essential if the aid system is to remain both effective and sustainable.

Considerations of political alignment between donor and recipient may come in the way of a more efficient allocation. Future research could usefully explore the political economy of aid allocation in the aftermath of natural disasters accounting for recipient constraints in absorptive capacity. Another promising avenue for future research is to examine whether improvements in state capacity act as a form of macroeconomic "insurance," reducing vulnerability to climate-driven shocks and shaping donor responses in turn. Ultimately, the challenge for the international community is not only to respond to disasters, but to help countries withstand them. As climate risks intensify, the case for rebalancing aid toward resilience becomes increasingly compelling. The sustainability of the global aid architecture may well depend on whether this shift happens in time.

Data Availability

The data underlying this article are available in publicly accessible repositories. Natural disaster data are drawn from EM-DAT - The international disaster database (Université Catholique de Louvain, Brussels). Bilateral aid data are from the *Development Assistance Committee (DAC) | OECD* *Creditor Reporting System | OECD*. Macroeconomic variables are drawn from the *World Bank's World Development Indicators | DataBank*

[Replication files, including the merged dataset and Stata code used to produce the figures and tables, are available from the corresponding author upon request and will be uploaded to a public data repository upon acceptance.]

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Appendix

[Figure 1]

[Figure 2]

[Figure 3]

[Figure 4]

[Figure 5]

[Figure 6]

[Figure 7]

[Figure 8]

[Table 1]

[Table 2]

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[Table 21]

"Sur quoi la fondera-t-il l'économie du monde qu'il veut gouverner ? Sera-ce sur le caprice de chaque particulier ? Quelle confusion ! Sera-ce sur la justice ? Il l'ignore."

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contact@ferdi.fr
+33 (0)4 43 97 64 60