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Foreign Aid Concentration and Natural Disasters

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Abstract: We examine the impact of natural disasters on the concentration of development aid, using country-level panel data. Employed disaster indices are purely based on physical intensities of disasters, thus overcome the common issue of endogeneity in natural disaster data. Countries receive more disaster-related foreign aid in the aftermath of natural catastrophes. Beyond that, natural disasters lead to a diversification of types of aid received and a diversification of the number of donors. This is true in the immediate aftermath of the disaster, and continues long after. Our findings are robust to additional controls, alternative estimators, measures and data. The literature on the fragmentation of aid shows that, typically, aid is less effective in promoting economic development when it comes from many sources and is spread over many programmes. The paper thus shows that, besides the negative effect on economic growth, natural disasters also have a negative impact on development aid.

JEL classification: F35; Q54

Key words: natural disasters; foreign aid

1. Introduction

Natural disasters hamper economic development (Cavallo & Noy, 2011; Klomp & Valckx, 2014). Natural disasters also attract foreign aid (Becerra, Cavallo, & Noy, 2014), aimed to offset the negative effects. We focus on the impact of natural disasters on the aid concentration of recipient countries. The paper shows that natural disasters lead to a diversification of aid received, in terms of both the number of donors contributing and the types of aid received. This is true in the immediate aftermath of the disaster, as expected, but continues long after. The literature on the fragmentation of aid shows that, typically, aid is less effective in promoting economic development when it comes from many sources and is spread over many programmes (Gehring, Michaelowa, Dreher, & Spörri, 2017; Kimura, Mori, & Sawada, 2012; Oh & Kim, 2015; Sumner & Glennie, 2015). The paper thus shows that, besides the negative effect of natural disasters on economic growth, natural disasters also have a negative impact on development aid. As far as we know, no one has explored the impact of natural disasters on aid concentration of aid recipient countries with respect to their aid portfolio/donor base before, thus, this study allows us to bridge a gap in the literature.

Disasters increase foreign aid considerably and poorer countries could cover approximately three fourths of disaster damages due to hurricanes through foreign aid from public sources alone (Yang, 2008). There is a plethora of studies to support the fact that natural disasters increase the magnitude of foreign aid received by affected countries owing to various donor motives (Becerra et al., 2014; Becerra, Cavallo, & Noy, 2015; Wei, Marinova, & Zhao, 2014; Wood & Wright, 2016). It is also well established that there is a higher probability for disaster affected countries to receive more foreign aid when the disaster news coverage is wide and when the disaster affected countries have close connections (historical, political, cultural or religious, etc.) with potential donors prior to the disaster (Olsen, Carstensen, & Høyen, 2003; Strömberg, 2007). When disasters occur, the affected countries become the centre of international media attention. This news coverage helps affected countries to reach priority lists of potential foreign aid donors. Disasters create a platform for politicians, activist groups and affected parties to lobby their appeals for aid and to raise awareness of their development needs among potential donor entities. Through this awareness, disasters ultimately become an indirect determinant of donor future allocation decisions. As a result, disasters attract more donors and also aid meant for development purposes other than disaster related matters leading to a reduction in aid concentration in recipient countries.

The existing literature also discusses the determinants of post natural disaster aid allocations across space and time. Specifically, using an event study analysis approach of post disaster aid-surges, Becerra et al. (2014) whilst arguing that aid-surges cover only 3% of the estimated damages due to natural disasters (despite the median increase in ODA by 18% compares to pre disaster flows), identify disaster intensity and country characteristics such as level of development, country size and magnitude of foreign reserves as key determinants of post disaster aid-surges.

It is obvious that natural disasters enhance aid aimed at emergency and disaster relief, and perhaps preparedness too. This aid supposedly facilitates speedy and smooth recovery and reconstruction after natural disasters. There is evidence also to suggest that past foreign aid flows suppress the political willingness to invest on disaster prevention and mitigation intentions (Raschky & Schwindt, 2016). It is also to be noted that Becerra et al. (2015) present some evidence of cross-sectorial substitution where donors sometime decrease aid aimed at other sectors in order to increase humanitarian aid given to the same recipient.

Constructing a Herfindahl-Hirschman index for donor concentration, which acts as a proxy for aid proliferation in recipient countries, Kimura et al. (2012) find that aid proliferation negatively affects economic growth, especially in Africa. As Aldasoro, Nunnenkamp, and Thiele (2010) point out, aid proliferation, donor fragmentation and the lack of coordination have been widely identified as serious problems for aid effectiveness. Oh and Kim (2015) also find that donor proliferation is harmful to the recipient's growth in the long run. Gehring et al. (2017) present evidence to confirm negative effect of fragmentation on aid effectiveness in terms of economic growth. Acharya, De Lima, and Moore (2006) show that aid proliferation and fragmentation cause unacceptably high direct and indirect transaction costs on many recipient countries. Further, Anderson (2012) shows that aid fragmentation or lack of aid concentration imposes significant costs on donors and raise the transaction costs of bilateral donors.

In this paper, we examine the impact of natural disasters on concentration of foreign aid categories and donor base of aid recipient countries. The expansion in aid portfolio materialises through more diversified categories (beyond disaster related categories) under which aid recipients receive charitable receipts. Donor base expands when the number of donor entities from whom a recipient receives donations is increased. The analysis uses a cross country panel data set covering the period from 1979 to 2010. Employed disaster indices are purely based on physical intensities of disasters, thus overcome common issue of endogeneity in natural disaster data. Findings suggest that natural disasters attract not only aid aimed at emergency, disaster relief and preparedness but also foreign aid under multiple other development categories such as education, healthcare, environmental protection, natural recourses, forestry, technology, industry, construction, energy, agriculture, social welfare, water, transportation, trade, political stability and financial development. As such, natural disasters expand recipient aid portfolio with respect to categories under which they receive foreign aid. Not only that, natural disasters increase the number of donors who donate aid to a recipient country reducing recipient's dependence on a single donor. So, this is an expansion in the recipient aid donor base / network in terms of number of donors. Further, natural disasters also reduce aid concentration with respect to aid categories and donors as measured by the Herfindahl-Hirschman index.

The rest of the paper proceeds as follows. Section 2 introduces data and the empirical methodology. Section 3 discusses results followed by robustness checks in section 4. Concluding section 5 discusses findings and policy implications of the study. It also points out limitations of the paper whilst suggesting potential avenues for further research in the future.

2. Empirical Analysis

2.1 Data

The source of foreign aid data for this study is the international aid data provided by AidData's Research Release 2.1 (Tierney et al., 2011). AidData is a project of the partnership among Brigham Young University, the College of William and Mary, and Development Gateway. "AidData defines development finance to include not only traditional Official Development Assistance (ODA) but also loans or grants from governments, official government aid agencies, and inter-governmental organisations intended mainly to promote the economic development and welfare (broadly defined) of developing countries…" (Tierney et al., 2011, p. 1892). However, AidData does not include funding from nongovernmental organisations, private investors, banks or foundations and military assistance. AidData covers information on development finance activities from 1946 - 2013. Aid Data has augmented the OECD Creditor Reporting System (CRS) database with more data gathered from donor annual reports, project documents from both bilateral and multilateral aid agencies, donor agency sources, and agency websites and databases.

The amount of aid used in this analysis is the commitment amount (in constant 2009 USD) the donor (donor country or the multilateral organisation) has agreed to provide for the duration of the project, often disbursed over the following years. AidData has developed a five digit coding system to identify the sector and purpose of the project. We use these codes to classify aid categories.

Other economic indicators and natural disaster data are taken from the ifo GAME database (Felbermayr & Gröschl, 2014). Natural disaster data are generally subject to criticism over the potential endogeneity issues as measures of natural disaster outcomes are often affected by socio and economic conditions of affected areas. Natural disaster data of ifo GAME are unique in the sense that they have been constructed purely based on the physical intensities of disasters so that the measures have entirely overcome the endogeneity problem.

The ifo GAME data presents two aggregated natural disaster indices, namely 'disindexla' (disaster index 1) and 'indexla' (disaster index 2). To compile these disaster indices physical intensity data of earthquakes, volcanic eruptions, storms, floods, droughts and extreme temperature events have been extracted from primary geophysical and meteorological databases. The physical intensity measure used for earthquakes is the maximum realisation value on the Richter scale within a single earthquake episode. The highest recorded Volcanic Explosivity Index (VEI) during a volcanic eruption has been used for volcanic intensity. The maximum total wind speed in knots on a country basis reflects storm intensity. Floods are measured as the positive difference in total monthly precipitation whilst droughts take value unity in an indicator variable if the rainfall is below 50% of the long-run monthly mean at least for three consecutive months or five months within a year, and zero otherwise (Felbermayr & Gröschl, 2014, pp. 94-95). All the disaster measures are aggregated into an overall composite disaster index.

Composite disaster indices, 'indexla' and 'disindexla' are the sum of physical intensity measures of different types of disasters occurred in a given country in a given year. Both indices are weighted by log area of that country appreciating the fact that economic effects of disasters vary with the extent of a country. 'Disindexla' is further weighted by respective inverse sample standard deviations. Use of the inverse of the standard deviation of a disaster type within a country over all years rules out that any single disaster component dominates the movement of disaster index (Felbermayr & Gröschl, 2014, p. 98).

Disaster index 'indexla' is created using an unweighted sum of disaster intensity measure after scaling for all respective disaster variables by land area. However, 'disindexla' further uses the inverse of the standard deviation of a disaster type within a country over all years as precision weights. Therefore, no single disaster component dominates the movement of the disaster index, 'disindexla'. For this reason, 'disindexla' appears to be a better index to represent natural disasters over 'indexla'. As such, more refined disaster index, 'disindexla' is used in this analysis.

In our analysis, the Herfindahl-Hirschman index (HHI) (Herfindahl, 1951; Hirschman, 1964) is employed to measure foreign aid concentration. The index which uses following formula varies between 0 and 1.

(1)

where is the Herfindahl-Hirschman index which measures aid concentration in country i for year t, is the share of donations received under category j or from donor j, and N is the number of categories or donors. An index value of one for the *HHI* which is constructed based on categories under which foreign aid is received by recipient countries ($HHI^{categories}$), represents a perfectly concentrated aid portfolio where the recipient receives entire foreign aid under one category. An index value close to zero represents an extremely diversified aid portfolio where the recipient receives a good spread of foreign aid under many more categories.

An index value of one for the Herfindahl-Hirschman index which is constructed based on donors from whom recipients receive foreign aid (HHI^{donors}) indicates a perfectly concentrated aid network where all the aid is received from the same donor. A value close to zero indicates donor diversification where single donor dependence is much less.

Table 1: Summary statistics (post estimation)

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Herfindahl-Hirschman Index, Aid Cat. ($HHI^{categories}$)	2,425	0.2804	0.2031	0.0794	1
Herfindahl-Hirschman Index for Donors (HHI^{donors})	2,183	0.3176	0.2302	0.0606	1
Disaster Index 1 (disindexla)	2,425	0.0317	0.1756	6.63e-06	2.228
Disaster Index 2 (indexla)	2,425	0.0323	0.1745	1.06E-06	2.155
GDP per capita, PPP (in logs)	2,183	7.847	1.127	5.491	11.238
Polity Index of Polity IV Project	2,183	0.582	0.333	0	1
Domestic Credit by Banking Sector (% of GDP)	2,183	0.460	0.377	-0.730	2.489
Current Account Balance (% of GDP)	2,183	-0.031	0.081	-0.448	0.446
Population (in logs)	2,183	9.485	1.456	6.915	14.096
No. of Aid Categories	2,183	14	4	1	18
No. of Donors	2,183	19	10	1	47
Total Amount, Aid Received (in constant 2009 US$)	2,425	1.53E+09	3.00E+09	1811.3	5.87E+10

Post estimation summary statistics for the variables used in the analysis are shown in Table 1. On average, Herfindahl-Hirschman index for aid categories ($HHI^{categories}$) is around 0.28 and Herfindahl-Hirschman index for donors (HHI^{donors}) is around 0.32 reflecting a moderately concentrated foreign aid portfolio / network. Disaster indices, 'disindexla' and 'indexla' take mean values of 0.0317 and 0.0323, respectively. Summary statistics of disaster indices 'disindexla' and 'indexla' are very similar. The reason for this is that these measures have been further scaled so that they admit the same mean to facilitate comparison (Felbermayr & Gröschl, 2014, p. 98). Countries receive aid from 19 donor entities on average in a country year. The minimum number of donors per country is 1 whilst the maximum number can be as high as 47. Meanwhile, they receive aid under 14 different categories, on average and the number of categories can vary between 1 and 18. These eighteen categories are emergency and disaster relief and preparedness; environmental protection; mining, metals and mineral resources; forestry; technology; industry; construction, real estate and urban planning; healthcare; education; energy; agriculture, livestock, food and fishing; social welfare; water; transportation; trade, economic and business policy; political; financial; and unclassifiable.

Figure 1 presents the variation of average aid per capita and average Herfindahl-Hirschman index for aid categories ($HHI^{categories}$) across countries. Figure 2 shows the variation of aid concentration measured by Herfindahl-Hirschman index for aid categories ($HHI^{categories}$) by countries over time.

Figure 1: Variation of aid across countries

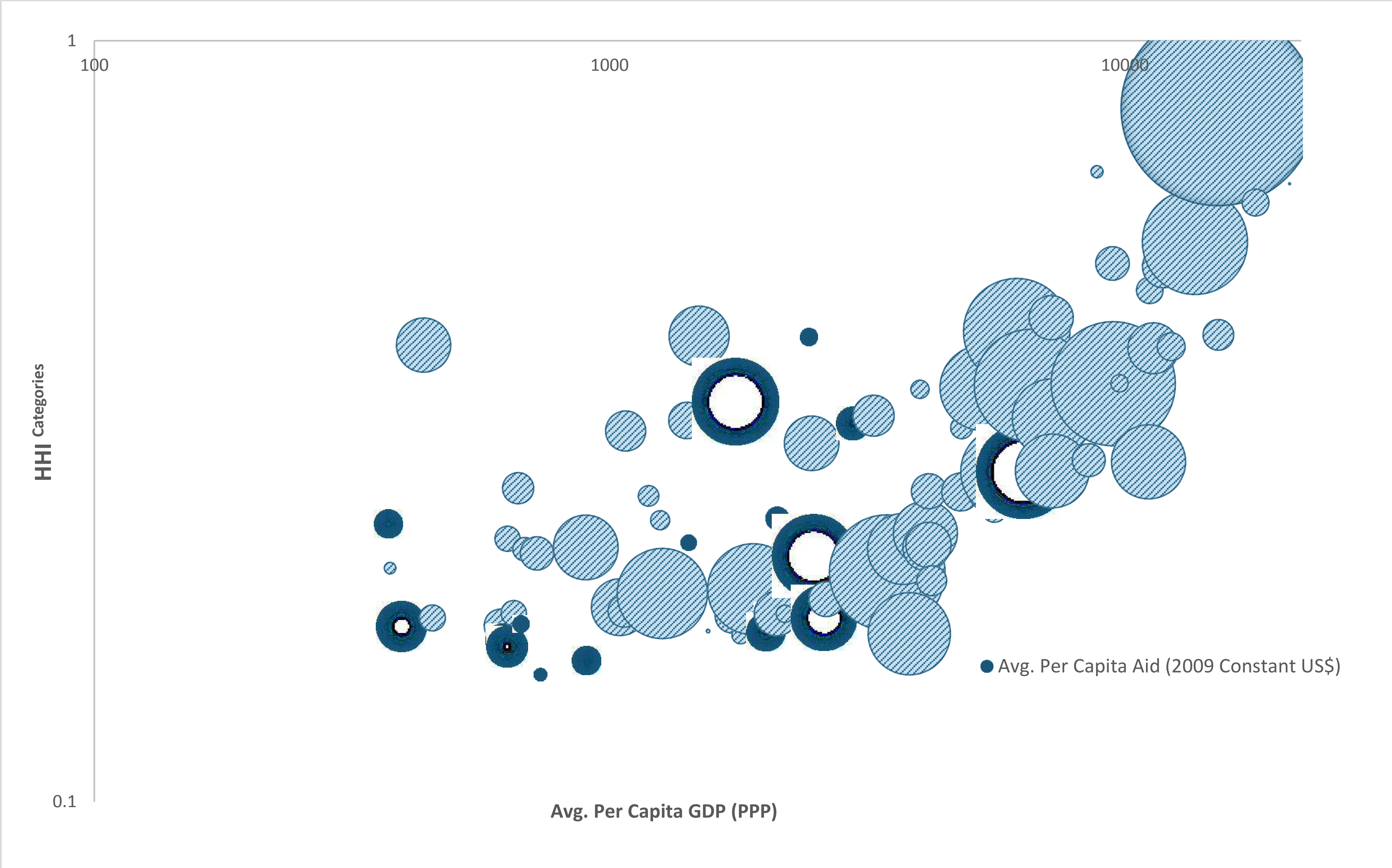
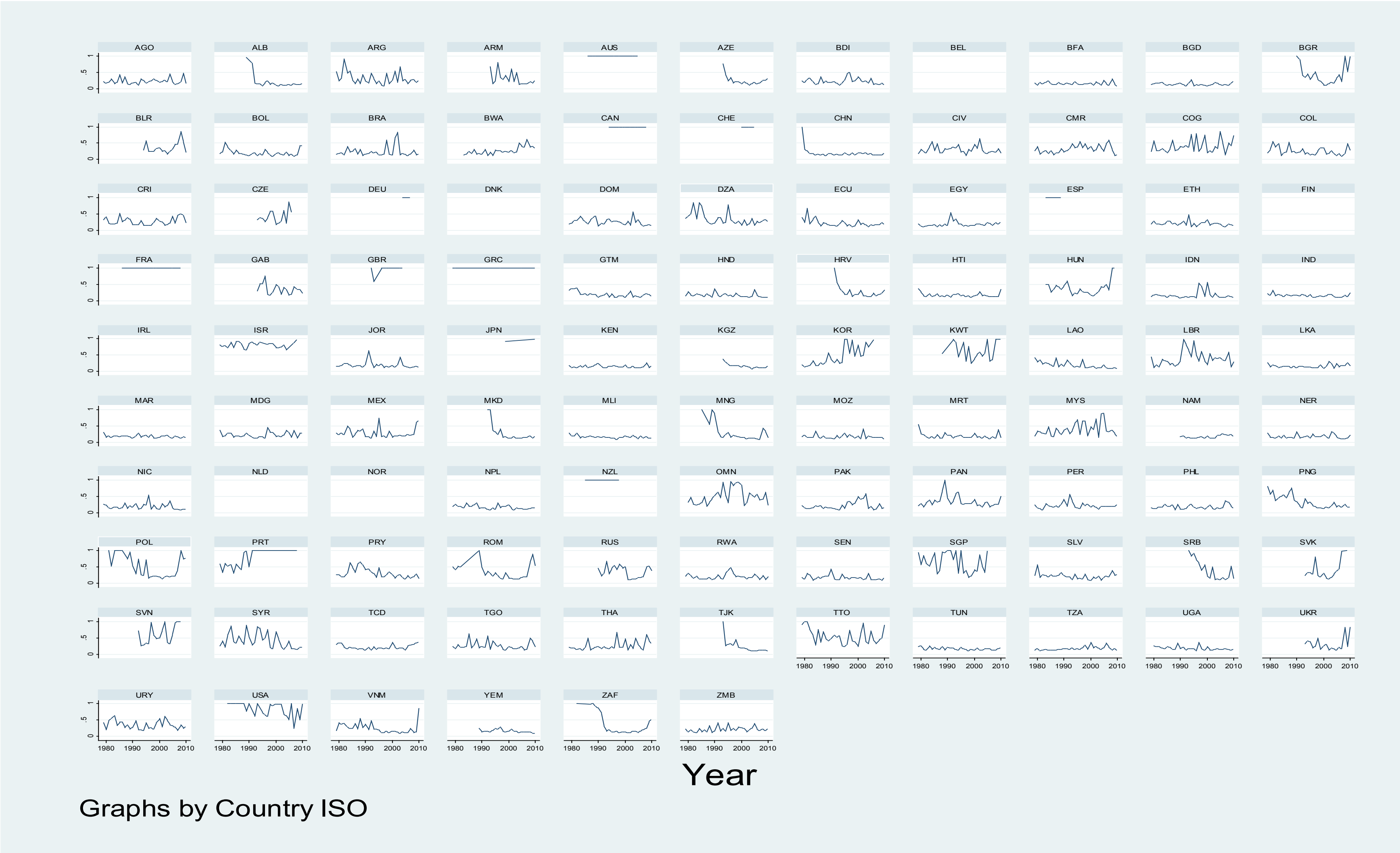


Figure 2: Variation of aid concentration measured by Herfindahl-Hirschman index for aid categories ($HHI^{categories}$) by countries over time



AGO	Angola
ALB	Albania
ARG	Argentina
ARM	Armenia
AUS	Australia
AZE	Azerbaijan
BDI	Burundi
BEL	Belgium
BFA	Burkina Faso
BGD	Bangladesh
BGR	Bulgaria
BLR	Belarus
BOL	Bolivia
BRA	Brazil
BWA	Botswana
CAN	Canada
CHE	Switzerland
CHN	China
CIV	Cote D'Ivoire
CMR	Cameroon
COG	Congo, Rep.
COL	Colombia
CRI	Costa Rica
CZE	Czech Republic
DEU	Germany
DNK	Denmark
DOM	Dominican Republic
DZA	Algeria
ECU	Ecuador
EGY	Egypt
ESP	Spain
ETH	Ethiopia
FIN	Finland
FRA	France
GAB	Gabon
GBR	United Kingdom
GRC	Greece
GTM	Guatemala
HND	Honduras
HRV	Croatia
HTI	Haiti
HUN	Hungary
IDN	Indonesia
IND	India
IRL	Ireland
ISR	Israel
JOR	Jordan
JPN	Japan
KEN	Kenya
KGZ	Kyrgyz Republic
KOR	Korea
KWT	Kuwait
LAO	Laos
LBR	Liberia
LKA	Sri Lanka
MAR	Morocco
MDG	Madagascar
MEX	Mexico
MKD	Macedonia, FYR
MLI	Mali
MNG	Mongolia
MOZ	Mozambique
MRT	Mauritania
MYS	Malaysia
NAM	Namibia
NER	Niger
NIC	Nicaragua
NLD	Netherlands
NOR	Norway
NPL	Nepal
NZL	New Zealand
OMN	Oman
PAK	Pakistan
PAN	Panama
PER	Peru
PHL	Philippines
PNG	Papua New Guinea
POL	Poland
PRT	Portugal
PRY	Paraguay
ROM	Romania
RUS	Russia
RWA	Rwanda
SEN	Senegal
SGP	Singapore
SLV	El Salvador
SRB	Serbia
SVK	Slovak Republic
SVN	Slovenia
SYR	Syria
TCD	Chad
TGO	Togo
THA	Thailand
TJK	Tajikistan
TTO	Trinidad & Tobago
TUN	Tunisia
TZA	Tanzania
UGA	Uganda
UKR	Ukraine
URY	Uruguay
USA	United States
VNM	Vietnam
YEM	Yemen
ZAF	South Africa
ZMB	Zambia

2.2 Empirical Model

We employ a panel regression estimator with country and year fixed effects as the main estimation tool in our analysis. The fixed effects estimator with time dummies takes care of country specific characteristics that do not change over time (unobservable heterogeneity) and time-variant shocks common to all countries.

The panel regression equation of the most parsimonious model is as follows:

(2)

where the foreign aid concentration as measured by Herfindahl-Hirschman index in country *i* for year *t*, is the dependent variable. This measure is based on the categories under which recipient countries receive foreign aid. *Dis* is our disaster index, 'disindexla' taken from the ifo GAME database. It is the sum of physical intensity measures of all natural disasters occurred in a specific country in a specific year weighted by land area of the affected country and respective sample standard deviations. This disaster measure is purely based on physical strengths of disasters. As such, it is expected to rule out in entirety, the potential endogeneity problem of disaster measure being affected by other economic indicators of the affected country.

It takes time for natural disasters to attract foreign aid, specifically aid aimed at other development categories rather than disaster related purposes. Further, disasters can occur at any time of the calendar year. Having considered these, lagged disaster index is included in the equation instead of the contemporaneous disaster index.

Terms and are the country and year fixed effects included in the model, respectively. The final term in the equation is the error term. As natural disasters are not evenly distributed across countries, robust standard errors are clustered at country level. However, when clustered at regional level considering potential spatial dependence, results do not change.

3. Results

Results of the baseline model are given in Table 2. We find statistically significant negative impact of natural disasters that occurred in the previous year on the recipient foreign aid category concentration as measured by Herfindahl-Hirschman index. The first disaster index, disindexla, is the sum of physical intensity measures of disasters took place in a specific country year weighted by the land area of that country and by respective inverse sample standard deviations.

Following Felbermayr and Gröschl (2014), we quantify the marginal aid concentration impact of disasters at different intensities. According to the results, in a year in which the disaster index is equal to the sample mean of 0.0317, aid concentration as measured by Herfindahl-Hirschman index is lower by about 0.0075 index points[1]; a one standard deviation increase of disaster index above the mean reduces aid concentration by about 0.0491 Herfindahl-Hirschman index points[2]. Hence, with disasters, the categories under which countries receive foreign aid would expand reducing aid concentration. It is obvious that disasters have a positive impact on disaster related aid as disasters attract aid aimed at disaster-connected matters. However, it appears that disasters increase not only disaster related aid but also other kinds of charitable receipts which would in turn affect the economic development of the recipient-country as per the existing literature.

Table 2: Results for regressing foreign aid concentration on natural disasters: Base model

	Dependent variable: Aid concentration ($HHI^{categories}$)
	Fixed Effects
Lagged Disaster Index 1 (disindexla)	-0.237***
	(0.0498)
Observations	2,425
Number of Countries	95
R^2	0.032

Notes: Annual data 1979-2010, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

[1] -0.237*0.0317

[2] -0.237*(0.0317+0.1756)

4. Robustness Checks

4.1 Without "Emergency and disaster relief and preparedness" Category

Our aid categories include the aid category related to natural disasters, i.e. "emergency and disaster relief and preparedness" category. To ensure that the results are not driven by this category, we re-estimate our base model with Herfindahl-Hirschman index calculated excluding this category. As apparent from results contained in Table 3 which are strongly consistent with of the base model, this exercise does not make any difference to the original findings.

Table 3: Results for regressing foreign aid concentration excluding "emergency and disaster relief and preparedness" category on natural disasters: Base model

	Dependent variable: Aid concentration ($HHI^{categories}$) excluding disaster related aid category
	Fixed Effects
Lagged Disaster Index 1 (disindexla)	-0.237***
	(0.0490)
Observations	2,423
Number of Countries	94
R^2	0.034

Notes: Annual data 1979-2010, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.2 Contemporaneous Disasters and Second Lag of Disasters

We have used lagged disaster variable in our base model for the reasons set out under 'Empirical Model'. As a further robustness check, we include contemporaneous disasters and a further lag of disasters to check how the model performs in the presence of these variables. Results are presented in Table 4. The impact of first lag of disasters does not dissipate once contemporaneous disasters and a further lag of disasters are included. Further, we cannot observe a statistically significant impact of contemporaneous disasters on the aid concentration, confirming the lagged effect of disasters on aid concentration.

Table 4: Results for regressing foreign aid concentration on natural disasters: Contemporaneous Disasters and Second Lag of Disasters (fixed effects)

	Dependent variable: Aid concentration (*HHI* ^{categories})		
	(1)	(2)	(3)
Disaster Index 1 (disindexla)		-0.0324	0.0649
		(0.0858)	(0.120)
L. Disaster Index 1 (disindexla)	-0.237***	-0.222***	-0.0982**
	(0.0498)	(0.0252)	(0.0391)
L2. Disaster Index 1 (disindexla)			-0.391***
			(0.108)
Observations	2,425	2,425	2,315
Number of Countries	95	95	92
R^2	0.032	0.032	0.034

Notes: Annual data 1979-2010, except where observations lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.3 Additional Controls

We gradually add more control variables to our very parsimonious base model to check the sensitivity of results. Control variables are added sequentially for easy perusal of their effect. As we can imagine income level as a determinant of aid concentration, we add logged gross domestic product (GDP) per capita (measured in constant purchasing power parity dollars) to the regression. As the political regime of a country plays a role in the aid attracted by that country, acknowledging that most foreign aid is politically influenced, the Polity index of Polity IV Project is added to the regression. As domestic credit disbursed by banking sector as a percentage of GDP indicates the availability of recovery finances and also the level of financial development of the country, credit variable is included in the regression. The dummy variable to the effect whether the country is a member country of OECD also reflects the close ties it has with big donors. Current account balance as percentage of GDP and population variables are also included in the regression equation as additional controls. Considering the time lag it takes for the influence of these controls to be fed into aid concentration, lagged terms of control variables are included in the regression.

As apparent from Table 5, the earlier results hold in the presence of other control variables, namely, per capita income, polity, domestic credit availability, being an OECD country, current account balance and population. So, even in the presence of these controls, disasters diversify aid with respect to aid categories.

4.4 *Alternative Estimators*

As a further robustness check, we re-estimate the model with controls using ordinary least squares (OLS), difference and system generalised method of moments (GMM) estimators; see Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998) and (Roodman, 2009b). Results are presented in Table 6. All the alternative estimators yield statistically significant negative impact of natural disasters on foreign aid concentration.

Table 5: Results for regressing foreign aid concentration on natural disasters: Controls (Fixed Effects)

	Dependent variable: Aid concentration ($HHI^{categories}$)					
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged Disaster Index 1 (disindexla)	-0.225***	-0.216***	-0.226***	-0.226***	-0.227***	-0.234***
	(0.0544)	(0.0518)	(0.0504)	(0.0505)	(0.0571)	(0.0565)
Lagged GDP per capita (logged)	0.0273	0.0187	0.0411	0.0408	0.0609	0.0522
	(0.0392)	(0.0418)	(0.0385)	(0.0386)	(0.0410)	(0.0424)
Lagged Polity Index		-0.0642	-0.0351	-0.0361	-0.0313	-0.0329
		(0.0386)	(0.0328)	(0.0325)	(0.0330)	(0.0331)
Lagged Credit (% of GDP)			0.0810**	0.0815**	0.0623*	0.0603*
			(0.0345)	(0.0344)	(0.0347)	(0.0342)
Lagged OECD Dummy				0.0127	0.00816	-0.00194
				(0.0511)	(0.0524)	(0.0531)
Lagged Current Account Balance (% of GDP)					-0.100	-0.0961
					(0.0753)	(0.0743)
Lagged Population (in logs)						-0.0585
						(0.0766)
Observations	2,425	2,425	2,282	2,282	2,183	2,183
Number of Countries	95	95	94	94	94	94
R^2-	0.033	0.038	0.045	0.046	0.045	0.046

Notes: Annual data 1979-2010, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Results for regressing aid concentration on natural disasters: Alternative estimators

	Dependent variable: Aid concentration (*HHI* ^{categories})			
	(1)	(2)	(3)	(4)
	FE	OLS	Difference GMM	System GMM
Lagged Disaster Index 1 (disindexla)	-0.234***	-0.234***	-0.430***	-0.355***
	(0.0565)	(0.0577)	(0.103)	(0.126)
Lagged GDP per capita (logged)	0.0522	0.0522	0.0857	0.160
	(0.0424)	(0.0434)	(0.178)	(0.111)
Lagged Polity Index	-0.0329	-0.0329	0.00674	-0.0209
	(0.0331)	(0.0338)	(0.100)	(0.0783)
Lagged Credit (% of GDP)	0.0603*	0.0603*	0.0910	0.218**
	(0.0342)	(0.0350)	(0.0890)	(0.0994)
Lagged OECD Dummy	-0.00194	-0.00194	-0.524	0.740**
	(0.0531)	(0.0543)	(0.333)	(0.365)
Lagged Current Account Balance (% GDP)	-0.0961	-0.0961	0.199	0.174
	(0.0743)	(0.0760)	(0.148)	(0.133)
Lagged Population (in logs)	-0.0585	-0.0585	-0.994***	-0.104
	(0.0766)	(0.0783)	(0.278)	(0.0745)
Observations	2,183	2,183	2,065	2,183
Number of Countries	94		92	94
R^2	0.046	0.544		
Number of Instruments			85	91
Arellano-Bond test AR(1)			0.000	0.000
Arellano-Bond test AR(2)			0.319	0.134
Hansen Test			0.683	0.551

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 No. of lags used to instrument the endogenous variables in difference and system GMM regressions limited to 10 starting at lag 2.

4.5 *Alternative Aid Measures*

Apart from Herfindahl-Hirschman index, we use other indicators which represent aid diversity as the dependent variable. The results of these models are given in Table 7. Natural disasters as measured by disaster index, 'disindexla', have a statistically significant positive impact on the number of aid categories under which recipients receive foreign aid (Column 1 of Table 7). This indicates an enhancement in the diversification of the recipient aid portfolios. Natural disasters also significantly increase the number of donor entities donating to a given recipient (Column 2 of Table 7). This reflects an enhancement in the diversification across aid sources, i.e., donors. Natural disasters also reduce the dependence of a single donor as reflected by the negative effect of the disaster index on Herfindahl-Hirschman index of donors (Column 3 of Table 7). Thus, disasters expand the aid donor network of recipient countries enabling disaster prone countries to attract more aid inflows. When we use total amount of aid received by a recipient (in constant 2009 US$) as the dependent variable, the sign on the yielded coefficient is positive although it is not statistically significant (Column 4 of Table 7). However, when we use the other composite disaster index, 'indexla' (a less refined disaster measure as it has not been weighted by the inverse of the respective sample standard deviations, as discussed above) presented by Felbermayr and Gröschl (2014), we can see a statistically significant positive impact of natural disasters on total amount of aid (Column 5 of Table 7).

4.6 *Alternative Disaster Data, EM-DAT International Disaster Database*

As a further robustness check, we use a disaster measure calculated using disaster data obtained from EM-DAT, the International Disaster Database (Guha-Sapir, Below, & Hoyois, 2014) and re-estimate our base model. In this exercise, disasters are measured as the percentage of population affected due to all natural disasters during a country year thus it captures humanitarian motives also for foreign aid allocation by donors apart from disaster intensity. Earlier results hold; see Table 8. We repeat the analysis using the EM-DAT disaster measure constructed excluding biological disasters for better comparison with the ifo GAME data disaster indices as these composite physical intensity disaster indices do not include biological disasters. Unreported results are almost identical to the ones in Table 8.

Table 7: Results for regressing foreign aid concentration and other aid measures on natural disasters: Alternative measures for foreign aid (Fixed Effects)

	Dependent variable: Foreign aid measure				
	(1) No. of Aid Categories	(2) No. of Aid Donors	(3) Aid Concentration (HHI^{donors})	(4) Aid - Total Amount (2009 US$)	(5) Aid - Total Amount (2009 US$)
Lagged Disaster Index 1 (disindexla)	5.391*** (0.429)	9.001*** (1.963)	-0.185*** (0.0500)	2.235e+08 (3.368e+08)	
Lagged Disaster Index 2 (indexla)					5.225e+08** (2.614e+08)
Observations	2,425	2,425	2,425	2,425	2,425
Number of Countries	95	95	95	95	95
R^2	0.330	0.745	0.054	0.037	0.037

Notes: Annual data 1979-2010, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Results for regressing foreign aid concentration on natural disasters: Alternative disaster data, EM-DAT (Fixed Effects)

	Dependent variable: Aid concentration
	HHI ^{categories}
Lagged % of population affected due to all natural disasters	-0.000542*
	(0.000292)
Observations	4,729
Number of Countries	0.042
R^2	190

Notes: Annual data 1979-2010, except where first observation lost due to lags. Model includes a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

5. Long Run Effects

To test whether the impact of natural disasters on aid concentration extends to long run, we repeat our analysis with long differences of independent variables. Accordingly, we regress aid concentration on five year differences of independent variables and thereafter on ten year differences. We observe statistically significant negative impact of disasters on aid concentration on both occasions confirming that the impact is not limited only to short run; see Table 9.

Table 9: Results for regressing aid concentration on natural disasters: Long differences (FE)

	Dependent variable: Aid concentration (*HHI* ^{categories})	
	(1)	(2)
	5 Years	10 Years
Differenced Disaster Index 1 (disindexla)	-0.167***	-0.410***
	(0.0250)	(0.0471)
Differenced GDP per capita (logged)	-0.0971***	-0.0390
	(0.0346)	(0.0340)
Differenced Polity Index	-0.0234	-0.0436*
	(0.0279)	(0.0234)
Differenced Credit (% of GDP)	0.0455*	0.0551
	(0.0246)	(0.0375)
Differenced OECD Dummy	-0.0950*	-0.196**
	(0.0481)	(0.0900)
Differenced Current Account Balance (% GDP)	0.181***	0.116*
	(0.0617)	(0.0674)
Differenced Population (in logs)	-0.263	-0.130
	(0.162)	(0.136)
Observations	1,784	1,356
Number of Countries	93	90
R^2	0.057	0.083

Notes: Annual data 1979-2011, except where first observation lost due to lags. All models include a constant term, country and year fixed effects. Errors clustered at the country level. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

6. Discussion and Conclusion

We explore the impact of natural disasters on foreign aid concentration of aid recipient countries. The disaster indices used are purely based on physical intensities of disasters, so our study overcomes the common issue of endogeneity in natural disaster data. We find that natural disasters increase the number of development categories under which recipient countries receive charitable receipts. We also find that natural disasters increase the number of donor entities from whom disaster affected countries receive foreign aid. These results hold in the presence of additional controls such as per capita income, trade openness, political regime, domestic credit, foreign direct investments, etc. Apart from panel fixed effects estimator, alternative estimators, namely, OLS, difference and system GMM also yield consistent results. Results are also robust to alternative aid measures, disaster measures and data. Besides the short run effects, our study also finds evidence of long run disaster impact on foreign aid concentration.

Aid furthers economic development. One may think that any expansion in the donor base of recipient countries would facilitate the economic development of recipient countries with a supportive and robust external network. However, existing literature has identified aid proliferation as an impediment for economic development in recipient countries mainly due to the huge transaction and administrative costs imposed in recipient country's government and "inefficiency of the overburdened bureaucracy" (Gehring et al., 2017, p. 322). Other studies also found a negative effect of aid diversification on development (Kimura et al., 2012; Oh & Kim, 2015; Sumner & Glennie, 2015).

Accordingly, natural disasters can indirectly affect the development of countries through increased aid concentration. This adds to the mechanisms through which natural disasters affect development (Cavallo, Galiani, Noy, & Pantano, 2013; Cavallo & Noy, 2011; Keerthiratne & Tol, 2017; Klomp, 2014; Klomp & Valckx, 2014; Noy, 2009). Thus, policy makers in disaster-vulnerable countries, and their donors, should be aware of the link between natural disasters and aid concentration to avoid action to make a destructive calamity worse.

Our study does not identify the exact mechanisms through which natural disasters influence aid concentration; or how different forms of aid concentration affect economic development. We therefore do not know how different policies could minimize the negative effects of disaster aid while supporting disaster relief and recovery. Future research can address these issues.

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Bibliography

Acharya, A., De Lima, A. T. F., & Moore, M. (2006). Proliferation and fragmentation: Transactions costs and the value of aid. *The journal of development studies, 42*(1), 1-21.

Aldasoro, I., Nunnenkamp, P., & Thiele, R. (2010). Less aid proliferation and more donor coordination? The wide gap between words and deeds. *Journal of International Development, 22*(7), 920-940.

Anderson, E. (2012). Aid fragmentation and donor transaction costs. *Economics Letters, 117*(3), 799-802. doi: https://doi.org/10.1016/j.econlet.2012.08.034

Arellano, M., & Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies, 58*, 277-297.

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics, 68*(1), 29-51. doi: 10.1016/0304-4076(94)01642-D

Becerra, O., Cavallo, E., & Noy, I. (2014). Foreign aid in the aftermath of large natural disasters. *Review of Development Economics, 18*(3), 445-460. doi: 10.1111/rode.12095

Becerra, O., Cavallo, E., & Noy, I. (2015). Where is the money? Post-disaster foreign aid flows. *Environment and Development Economics, 20*(5), 561-586. doi: 10.1017/S1355770X14000679

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics, 87*(1), 115-143.

Cavallo, E., Galiani, S., Noy, I., & Pantano, J. (2013). Catastrophic natural disasters and economic growth. *Review of Economics and Statistics, 95*(5), 1549-1561.

Cavallo, E., & Noy, I. (2011). Natural disasters and the economy - A survey. *International Review of Environmental and Resource Economics, 5*(1), 63-102.

Felbermayr, G., & Gröschl, J. (2014). Naturally negative: The growth effects of natural disasters. *Journal of Development Economics, 111*, 92-106. doi: http://dx.doi.org/10.1016/j.jdeveco.2014.07.004

Gehring, K., Michaelowa, K., Dreher, A., & Spörri, F. (2017). Aid Fragmentation and Effectiveness: What Do We Really Know? *World Development, 99*, 320-334. doi: 10.1016/j.worlddev.2017.05.019

Guha-Sapir, D., Below, R., & Hoyois, P. (2014). *EM-DAT: International Disaster Database - www.emdat.be - Université Catholique de Louvain, Brussels, Belgium.*

Herfindahl, O. C. (1951). *Concentration in the Steel Industry.* (PhD Thesis), Department of Economics, Colombia University.

Hirschman, A. O. (1964). The Paternity of an Index. *The American Economic Review, 54*(5), 761-762.

Keerthiratne, S., & Tol, R. S. J. (2017). Impact of Natural Disasters on Financial Development. *Economics of Disasters and Climate Change, 1*(1), 33-54. doi: 10.1007/s41885-017-0002-5

Kimura, H., Mori, Y., & Sawada, Y. (2012). Aid Proliferation and Economic Growth: A Cross-Country Analysis. *World Development, 40*(1), 1-10. doi: http://dx.doi.org/10.1016/j.worlddev.2011.05.010

Klomp, J. (2014). Financial fragility and natural disasters: An empirical analysis. *Journal of Financial Stability, 13*, 180-192.

Klomp, J., & Valckx, K. (2014). Natural disasters and economic growth: A meta-analysis. *Global Environmental Change, 26*(1), 183-195.

Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development Economics, 88*(2), 221-231.

Oh, J., & Kim, Y. (2015). Proliferation and fragmentation: uphill struggle of aid effectiveness. *Journal of Development Effectiveness, 7*(2), 192-209. doi: 10.1080/19439342.2014.983537

Olsen, G. R., Carstensen, N., & Høyen, K. (2003). Humanitarian crises: What determines the level of emergency assistance? Media coverage, donor interests and the aid business. *Disasters, 27*(2), 109-126.

Raschky, P. A., & Schwindt, M. (2016). Aid, Catastrophes and the Samaritan's Dilemma. *Economica, 83*(332), 624-645. doi: 10.1111/ecca.12194

Roodman, D. (2009b). How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata Journal, 9*(1), 86-136.

Strömberg, D. (2007). Natural disasters, economic development, and humanitarian aid. *The Journal of Economic Perspectives, 21*(3), 199-222.

Sumner, A., & Glennie, J. (2015). Growth, Poverty and Development Assistance: When Does Foreign Aid Work? *Global Policy, 6*(3), 201-211. doi: 10.1111/1758-5899.12251

Tierney, M. J., Nielson, D. L., Hawkins, D. G., Roberts, J. T., Findley, M. G., Powers, R. M., . . . Hicks, R. L. (2011). More dollars than sense: Refining our knowledge of development finance using AidData. *World Development, 39*(11), 1891-1906.

Wei, J., Marinova, D., & Zhao, D. (2014). Disaster assistance: Determinants of countries around the world contributing towards disaster donations. *International Journal of Emergency Management, 10*(1), 48-66. doi: 10.1504/IJEM.2014.061661

Wood, R. M., & Wright, T. M. (2016). Responding to Catastrophe: Repression Dynamics Following Rapid-onset Natural Disasters. *Journal of Conflict Resolution, 60*(8), 1446-1472. doi: 10.1177/0022002715596366

Yang, D. (2008). Coping with disaster: The impact of hurricanes on international financial flows, 1970-2002. *The BE Journal of Economic Analysis & Policy, 8*(1), 13.