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Research article

Donor interactions in the allocation of adaptation aid: A network analysis

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ABSTRACT

This article examines how adaptation aid is allocated across countries, and specifically focus on the role of donor—donor interactions in allocation decisions. We test two contrasting hypotheses: the presence of other adaptation donors in a recipient country may *increase* or *reduce* the likelihood of donor *i* to provide adaptation aid to that recipient. In the former case, donors support adaptation in the *same* recipient countries; in the latter, they provide their adaptation aid to *different* recipient countries. We model adaptation aid allocations as a *network*, and apply an innovative method, bipartite temporal exponential random graph models, to bilateral adaptation aid flows between 2010 and 2016. Our empirical analysis finds strong evidence for donor interactions. The results suggest a positive effect of other donors: donors tend to support adaptation in similar sets of recipient countries. These results provide further evidence that adaptation aid largely follow the structures and processes of traditional development aid, which poses questions for the additionality of finance for adaptation to climate change.

1. Introduction

A central dimension of climate justice concerns finance, especially for adaptation to the adverse effects of climate change: Industrialised countries, historically responsible for most greenhouse gas emissions, should help developing countries that have contributed minimally to anthropogenic climate change but suffer disproportionately from its impacts. Accordingly, the 1992 United Nations Framework Convention on Climate Change (UNFCCC) promises assistance for 'particularly vulnerable' developing countries to deal with climate change impacts (UNFCCC, 1992). The 2009 Copenhagen Accord as well as the Paris Agreement confirm this pledge (UNFCCC, 2009, 2015). Although much of this assistance comes from public development budgets (Weikmans, 2016), adaptation finance is conceptually different from traditional development aid: it reflects the responsibility of industrialised countries, and recognises that adapting to climate change is an additional burden for developing countries, which hence require new and additional resources (Pickering and Rübbelke, 2014; Scoville-Simonds, 2016; Weikmans, 2016).

Accordingly, adaptation finance should also follow a different allocation logic; most importantly, and in line with the UNFCCC regime, it should benefit primarily countries that are vulnerable to climate change. In practice, studies of adaptation aid allocation find only limited evidence that donors target their adaptation aid at vulnerable countries. Some studies find no, or even a negative, relationship, between a country's (or region's) vulnerability to climate change and the likelihood and/or level of adaptation aid (Barrett, 2015; Doshi and Garschagen, 2020; Robertsen et al., 2015; Robinson and Dornan, 2017; Saunders, 2019). Others analyses are more optimistic and suggest that countries more likely to suffer from biophysical climate risks tend to receive more support for adaptation, although at the same time, countries that are *less* vulnerable because their adaptive capacity and adaptation 'readiness' is higher, similarly tend to receive more adaptation support (Betzold and Weiler, 2016, 2017; Mori et al., 2019; Weiler et al., 2018). These results highlight a tension between equity and efficiency (Chen et al., 2018). Beyond vulnerability, studies have focused on a diverse range of determinants, including (*i*) other recipient characteristics, such as their income or level of democracy; (*ii*) donor characteristics, such as the ministry involved in allocation decisions (Peterson and Skovgaard, 2019); and (*iii*)

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recipient–donor relations, such as the level of trade between a donor and a recipient, a colonial past, or common political interests. We here focus on a fourth determinant: donor–donor relations. It seems very plausible that donors take into account the aid allocation decisions of their peers. In other words, how donor *i* distributes its adaptation aid probably influences how donor *j* distributes its adaptation aid in turn.

While such interaction effects between donors are plausible, they have rarely been studied (Calleja and Rowlands, 2015; Powell and Bobba, 2006). Some studies of aid allocation indirectly take into account donor interaction by controlling for the total amount of aid from all donors that recipients receives (Berthélemy, 2006b; Berthélemy and Tichit, 2004; Tarp et al., 1998; Tezanos Vázquez, 2008), and a few explicitly focus on donor interactions (Calleja and Rowlands, 2015; Davies & Klasen, 2013, 2019; Frot and Santiso, 2011). Theoretically, these studies identify two contrasting effects: On the one hand, the presence of other donors may *increase* the likelihood of donor *i* of also investing in *r*; this would mean donors focus their assistance on the same set of recipients. On the other hand, there are also reasons to expect the opposite: the presence of other donors in recipient *r reducing* the likelihood of donor *i* of also investing in *r*. Instead, donor *i* would turn to recipient *s*. This would lead to a 'division of recipients' among donors. Which of these effects, if any, we observe for adaptation finance remains an empirical question.

By conceptualising adaptation aid allocation as a *network* in which the provision of adaptation aid is a network tie, we can directly assess donor interactions. We therefore obtain a fuller picture of allocation patterns than we would with dyadic regression analysis, particularly because network models allow us to study interactions between actors in the network (Swiss, 2017; Ward et al., 2011). This allows us to including endogenous (network) dependencies, which more conventional models – assuming conditional independence – might omit and therefore risk biased estimates (Cranmer et al., 2017). Our analysis thus contributes to both to the climate finance and development aid literatures, in two ways: Theoretically, we focus attention to a hitherto neglected explanation of aid allocation, donor–donor relations. Empirically, we apply a newly developed network model, Temporal Exponential Random Graph Models (TERGMs), and conceptualise adaptation aid allocation as a network.

2. Literature review and expectations

The general development aid literature indicates that donors tend to concentrate their assistance on the same set of recipients (Swiss, 2017). A study of OECD aid between 1972 and 2003 finds that "no fewer than 28 recipients received aid from all 22 donors in the database" (Powell and Bobba, 2006, p. 5). Another study finds that the median recipient interacted with 23 different donors in 2000 (Acharya et al., 2006). Why does this donor proliferation occur and even increase (Acharya et al., 2006; Annen and Moers, 2012)? From a donor perspective, focusing on the same recipients as other donors is rational, for at least three reasons.

First, donors can 'free ride' or piggyback on the efforts of other donors. If there are already other development projects in a recipient country, these projects will have built infrastructure and capacity on which additional donors can build. For example, if donor *i* already implemented an adaptation project in recipient *r*, *r*'s 'adaptation readiness' is presumably higher and donor *j* can more easily implement its own adaptation project in turn. Accordingly, studies find a decline in the level of aid to a specific recipient as the number of other active donors increases (Chong and Gradstein, 2008; Knack and Rahman, 2007; Steinwand, 2015; Swiss, 2017).

Second, other donors' allocation decisions serve as a signal: A donor's giving aid to a recipient provides important information about that recipient to other donors, notably the recipient's absorptive capacity. Donor *i*'s provision of aid to recipient *r* signals to donor *j* that recipient *r* seems trustworthy and capable of using aid efficiently and effectively (Barthel, 2013; Davies and Klasen, 2019; Olivié and Pérez, 2016). Several studies find evidence for this 'bandwagon effect', where donors increase their aid to a recipient in response to positive allocation decisions of other donors (Berthélemy, 2006a; Tarp et al., 1998; Tezanos Vázquez, 2008). In particular, there is evidence that smaller donors follow the allocation decisions of large donors (Davies and Klasen, 2019; Fleck and Kilby, 2006; Hickmann, 1993).

Third, donors compete with each other for political influence and economic benefits through aid. Recipient countries that are important markets, for example, receive support from several donors, all of which seek to obtain beneficial access to this market. Donors that compete for export markets have been found to provide aid to the same recipients (Barthel, 2013; Fuchs et al., 2015). Donor competition inherently results in aid fragmentation (Annen and Moers, 2012; Powell and Bobba, 2006; Steinwand, 2015).

We expect similar considerations for the case of adaptation aid, that is, a concentration of adaptation aid on the same set of recipients. In other words, if many donors provide adaptation aid to recipient *r*, it is likely that donor *i* also supports adaptation in recipient *r*.

H1. The likelihood of donor *i* providing adaptation aid to recipient *r increases* with the number of other donors already providing adaptation aid to *r*.

Concentrating aid to the same set of recipients has well-documented negative effects (Berthélemy and Tichit, 2004; Dreher and Michaelowa, 2010) that a 'division of recipients' could alleviate. The presence of multiple donors, each with their own missions and reporting requirements, imposes high transaction costs on recipients that already struggle with scarce administrative resources. Fewer donors mean recipients can concentrate their limited resources on a smaller set of interlocutors and have fewer, and less divergent, reporting requirements (Acharya et al., 2006; Aldasoro2010; Arimoto and Kono, 2009; Djankov et al., 2009; Dreher and Michaelowa, 2010; Steinwand, 2015). Further, when many donors are present in a country, efforts are duplicated and responsibility is diffused. As a result, no single donor will feel responsible for the recipient's economic and social development, corruption may worsen, and aid become inefficient and ineffective (Acharya et al., 2006; Bourguignon and Platteau, 2013; Djankov et al., 2009; Dreher and Michaelowa, 2010; Jinhwan and Yunjeong, 2015; Knack and Rahman, 2007). Fewer donors reduce the risk of diffused responsibility and hence may improve aid governance and thereby increase aid effectiveness (Acharya et al., 2006; Bigsten and Tengstam, 2015; Bourguignon and Platteau, 2013; Nunnenkamp et al., 2013). Accordingly, donors have repeatedly committed to coordinating their aid activities to increase aid effectiveness, including in the 2005 Paris Declaration on Aid Effectiveness, the 2008 Accra Agenda for Action, or the EU's Code of Conduct on Complementarity and the Division of Labour in Development Policy (EU, 2011; OECD, 2008).

Beyond a general concern in increasing efficiency and effectiveness at the aggregate level, a division of recipients could also increase the influence of individual donors. Calleja and Rowlands (2015, p. 17) note that "based on the understanding that aid orphans, by definition, are not attracting large aid inflows, influence-seeking donors acting in self-interest should theoretically view aid orphans as a location to extract an additional benefit from aid at a relatively lower cost". Accordingly, even if donors do not seek to collectively maximise the impact of their aid, donors may want to provide aid to recipients where other donors are not present as they can relatively easily obtain that recipient's support and need not compete with other donors' aid. Instances of lead donorship, where one donor is continuously by far the primary donor in the recipient country, could be seen as cases of successful coordination (Lebovic, 2005; Steinwand, 2015).

These considerations would suggest a second, contrasting, hypothesis for the case of adaptation. If donors seek to collectively support the largest number of vulnerable countries, and maximise the impact of their adaptation aid, they should 'divide' recipients among themselves. Similarly, if donors seek to 'buy' support and maximise their influence in a recipient country, they should turn to recipients where few other donors are present. In other words, the presence of other donors in recipient *r reduces* the likelihood of donor *i* also investing in adaptation in this country.

H2. The likelihood of donor *i* providing adaptation aid to recipient *r decreases* with the number of other donors already providing adaptation aid to *r*.

3. Materials and methods

3.1. Dependent variable

Our analysis focuses on bilateral adaptation aid from 2010 through 2016, as bilateral public adaptation finance ('adaptation aid') represents the vast majority of adaptation finance mobilised to date (Victor, 2013). To test whether the presence of other adaptation donors in a recipient country affects the decision of donor *i* to also allocate adaptation aid to that recipient using bilateral, we model adaptation aid allocation as a network. As mentioned earlier, the use of a network of donor-recipient interactions allows us to model dependency structures in the network, such as whether aid allocation decisions by one donor influence the decisions of others. This ability of network models to capture interdependencies goes well beyond conventional regression models – including multilevel models able to account for certain interdependencies within clusters – and are therefore more realistic and less likely to introduce bias (Cranmer et al., 2017).

Our basic dependent variable consists of seven annual network capturing donor–recipient relationships in the period 2010 through 2016; for each year, we have a network $\mathbf{Y}$ for which the individual dyads Y_{ir} take on the value 1 when donor *i* committed adaptation aid to recipient *r*, and 0 otherwise. We transformed these basic networks into so-called two-mode (or bipartite) networks, which means that the vertices (representing actors) can be clearly divided into two separate disjoint and independent sets. This is clearly the case in our networks, as we have donor countries on the one hand, and recipients on the other. Thus, two-mode networks are more appropriate for our purpose as they exclude the many potential edges on the basic networks which are not theoretically possible (between two donors or two recipients). Jointly, these seven bipartite networks serve as our dependent variable. Further, we use the full (non-bipartite) networks for the seven years as a second specification of our dependent variable. This serves as both a robustness check and a test of the specific modelling technique for the bipartite networks. Our seven aid networks have 161 nodes (countries) each. This includes all countries that are included in the OECD Creditor Reporting System (CRS) as either donors or recipients for the entire period the study, except eleven countries where we have missing values.[1]

The OECD CRS provides project-level data on aid. Since 2009, the dataset classifies projecs as relevant for adaptation to climate change using the so-called 'Rio marker for adaptation'. The Rio Marker classifies a project as related to adaptation if "it intends to reduce the vulnerability of human or natural systems to the impacts of climate change and climate-related risks, by maintaining or increasing adaptive capacity and resilience" (OECD, 2011, p. 4). If a donor commits adaptation aid to a recipient country in a given year, this is recorded in the respective network as a tie. For modelling reasons, we only consider whether a donor committed adaptation aid to a recipient in a given year, but not how much the donor committed. As a result, we do not distinguish between projects where adaptation is the principal (main) objective, and projects where adaptation is only a significant objective (co-benefit), as the Rio marker does (OECD, 2011).

The OECD data have been repeatedly criticised (Kono and Montinola, 2019). The data relies exclusively on donors' own reporting, and several studies have found donors to over-report and mis-label projects as relevant for adaptation even when this relevance is unclear (Carter and le Comte, 2018; Donner et al., 2016; Junghans and Harmeling, 2012; Michaelowa and Michaelowa, 2011; Weikmans and Robert, 2017; Weikmans et al., 2017). Because of these problems, some discourage the use of OECD data for analysis (Kono and Montinola, 2019). On the other hand, there is at present simply no more comprehensive and comparable data on (adaptation) aid (Victor, 2013), and OECD data are widely used in the (adaptation) aid literature.

3.2. Independent and control variables

Two measures of centrality in the network—in-degree and out-degree——capture interaction effects. The former indicates the number of donors providing adaptation aid to a recipient; the latter the number of recipients that a donor assists with adaptation.[2] These terms are useful for modelling "popularity effects" (Hunter, 2007). We use the different terms from the R-package *ergm*. For the bipartite models (in which donors and recipient countries are separated by design), we implement the term *gwb1degree* for donors' out-degree, and *gwb2degree* for recipients' in-degree. In the full network models, we instead use the terms *gwidegree* and *gwodegree*, which are geometrically weighted measures of in-degree and out-degree over the entire network (and thus all countries in the model). These measures are constructed such that negative estimates reflect an *increased* likelihood of higher-degree nodes to form additional ties than would be predicted considering all other covariates. Put differently, a *negative* effect for the two in-degree measures indicates that a group of particularly 'popular' recipients receives support from a large number of donors (in line with H1). In contrast, a *positive* effect for in-degree indicates that recipients form less ties once they receive adaptation aid from a given donor (in line with H2). Similarly, for the out-degree measures, a negative effect indicates that a few donors are particularly active and provide adaptation aid to a wide range of recipient countries (H1), while a positive effect suggests that donors tend to focus their adaptation aid efforts on a small number of recipients (H2).

Donors may of course provide aid to the same set of countries because of characteristics that make them particularly attractive as recipients. They might be particularly vulnerable to climate change impacts, particularly efficient in using aid flows, or important

[1] Cook Islands, Cape Verde, Cuba, Kosovo, Niue, Nauru, North Korea, Saint Helena, Somalia, Syria, and Yemen are excluded.

[2] In network terminology, in-degree is the number of edges directed into a (developing country) vertex, and out-degree, the number of edges directed out of a (developed country) vertex.

economic partners or international political allies (see e.g. Weiler et al., 2018 for an overview of the determinants of adaptation aid allocation). We need to control for these other potential explanations of adaptation aid allocation so we can assess whether the presence of other donors affect allocation decisions *over and above* such explanations. First, we use the vulnerability score of the Global Adaptation Index (ND-GAIN) (ND-GAIN, n.d.); GDP per capita and its squared term (Alesina and Dollar, 2000), as reported by the World Bank (2018); and three dummy variables for countries considered 'particularly vulnerable': LDCs, SIDS, and African countries. Second, we include governance, measured by a combination of the six Worldwide Governance Indicators (Kaufmann et al., 2014). Third, we control for donors' economic and political interests by adding dyadic trade data (logged export values between all country pairs[3]) from the United Nations Statistics Division (2015); voting similarity in the UN General Assembly from Strezhnev and Voeten (2013); and a network of colonial ties which takes on the value of 1 if a country pair shares a colonial history, and 0 otherwise (Teorell et al., 2015).

Further, we control for a country's population size, as larger countries are more likely to receive aid (e.g. Younas, 2008). We also include a memory term, which indicates whether donors have given adaptation aid to the same recipients in the previous year. The term increases in size the less the network changes over the years (Leifeld and Cranmer, 2015). The memory term thus examines whether network ties from previous periods influence network formation in later years. As an additional measure of 'memory', we also include total development aid networks in the models. These networks measure how much development aid flowed between donor-recipient pairs in a given year, and allow us to estimate the relationship between conventional development aid and adaptation aid, which other studies have found to be connected (Betzold and Weiler, 2017; Robertsen et al., 2015; Weiler et al., 2018). The data are again from the OECD CRS. In the non-bipartite models, we control for whether a country is listed on Annex I of the UNFCCC and has climate finance commitments. This allows us to distinguish between donors and recipients in the network.[4] Lastly, we add some network statistics to the models (see below) to capture potential network dependency structures which might bias our estimates if not accounted for. The *edges* coefficient is a control for the overall density of ties in the network. Two other network statistic capture the likelihood that donors have zero ties (actor out-degree set to zero) and that recipients have no ties (actor in-degree set to zero).

3.3. Modelling strategy

Our data structure is problematic from a statistical point of view, as both the different networks for the various years and the dyads are very likely not independent of each other. We expect both the decisions of other donors as well as of donor *i*'s own past aid allocation to influence its present allocation decisions. One way to model such a data structure are Temporal Exponential Random Graph Models (TERGMs), which can explain tie formation while capturing both the network dynamics within a given year and cross-temporal correlations (Cranmer and Desmarais, 2011; Desmarais and Cranmer, 2012; Leifeld et al., 2018).

TERGMs are a suitable technique to model our repeated binary aid-allocation networks, and therefore work well to test our hypotheses about the probability of receiving adaptation aid. As mentioned earlier, we have two specifications for our seven adaptation aid networks: a bipartite (two-mode) specification in which the 31 donors are clearly separated from the 130 recipients; and a specification of the full networks of all 161 actors (countries), i.e. networks that do not *a priori* distinguish between donors and recipients.

To estimate our models, we rely on the R package *btergm* (Leifeld et al., 2018); confidence intervals are calculated using 1000 bootstrapping iterations. This model specification is, to the best of our knowledge, one of the very few applications of bipartite TERGMs so far implemented. One small drawback of these models is that the model statistics to capture main effects used in non-bipartite networks, i.e. *nodicov*, are not available for bipartite networks (Morris et al., 2008). Main effects basically capture the effects of the characteristics of nodes on tie formation, for instance the effect of recipient per capita GDP on the likelihood of adaptation aid allocation. In order to still be able to estimate these main effects, we generate networks for the donor-recipient pairs and assign the value of the recipient characteristic of interest to each pair, instead of assigning the values of these characteristics to the nodes (=countries). For example, the per capita GDP of recipient *j* in a given year is repeated on each edge it shares with one of the 31 donors. This setup is thus similar to a more conventional dyadic panel data structure.

To test the robustness our coding of the main effects in the bipartite networks, we also implement the full models, this time using the *nodeicov* term to capture the effects of the independent variables GDP per capita, vulnerability, governance, and total population. We do not change how we model the other independent variables in the model (total aid, exports from donors to recipients, UN voting patterns, and former colonial ties), as these variables are already dyadic in nature, and are implemented using the *edgecov* term in both the bipartite and the non-bipartite models (Morris et al., 2008).

In addition to all these terms, in the models using the full (non-bipartite) networks, we add one nodal attribute to differentiate between donors or recipients (using the Annex 1 dummy described above), which is not necessary in the bipartite models by design. To capture in-degree and out-degree, we include the terms *gwb1degree* and *gwb2degree* (see above) in the bipartite network model (the former for the degree of donors, the latter for the recipients). In the case of the full networks, we apply the equivalent terms *gwidegree* and *gwodegree*. Finally, in both models we include terms to capture the effect of isolated actors, i.e. actors not forming any ties in a given year, and an edge term counting the total number of edges in the aid networks. Overall, the two model specifications are similar and also serve to check the robustness of each other.

4. Results

4.1. Descriptive results

In a first step, let us look descriptively at patterns of adaptation aid flows. Fig. 1 lists for each recipient the average number of donors that have provided adaptation aid to that country in any year over the period of analysis (2010 through 2016). Overall, we have on average 860.4 donor-recipient relationships per year. If donors equally divided recipients among them, we would expect 6.6 adaptation donors per recipient and year. In practice, the number of adaptation donors present in a recipient country varies widely. Some countries only receive adaptation aid from a very limited number of donors (around four, but often also fewer); other countries receive adaptation aid from a much larger set of donors.

[3] We focus on exports instead of total trade flows since donors mostly care about their own economy.

[4] The models should pick up the difference between richer (donor) countries and poorer (recipient) countries and estimate the probability of tie formation between countries of the same group to be virtually zero, since in all of the annual networks there are no ties between countries of the same group (donor or recipient). The Annex I dummy supports the models in distinguishing between donors and recipients.

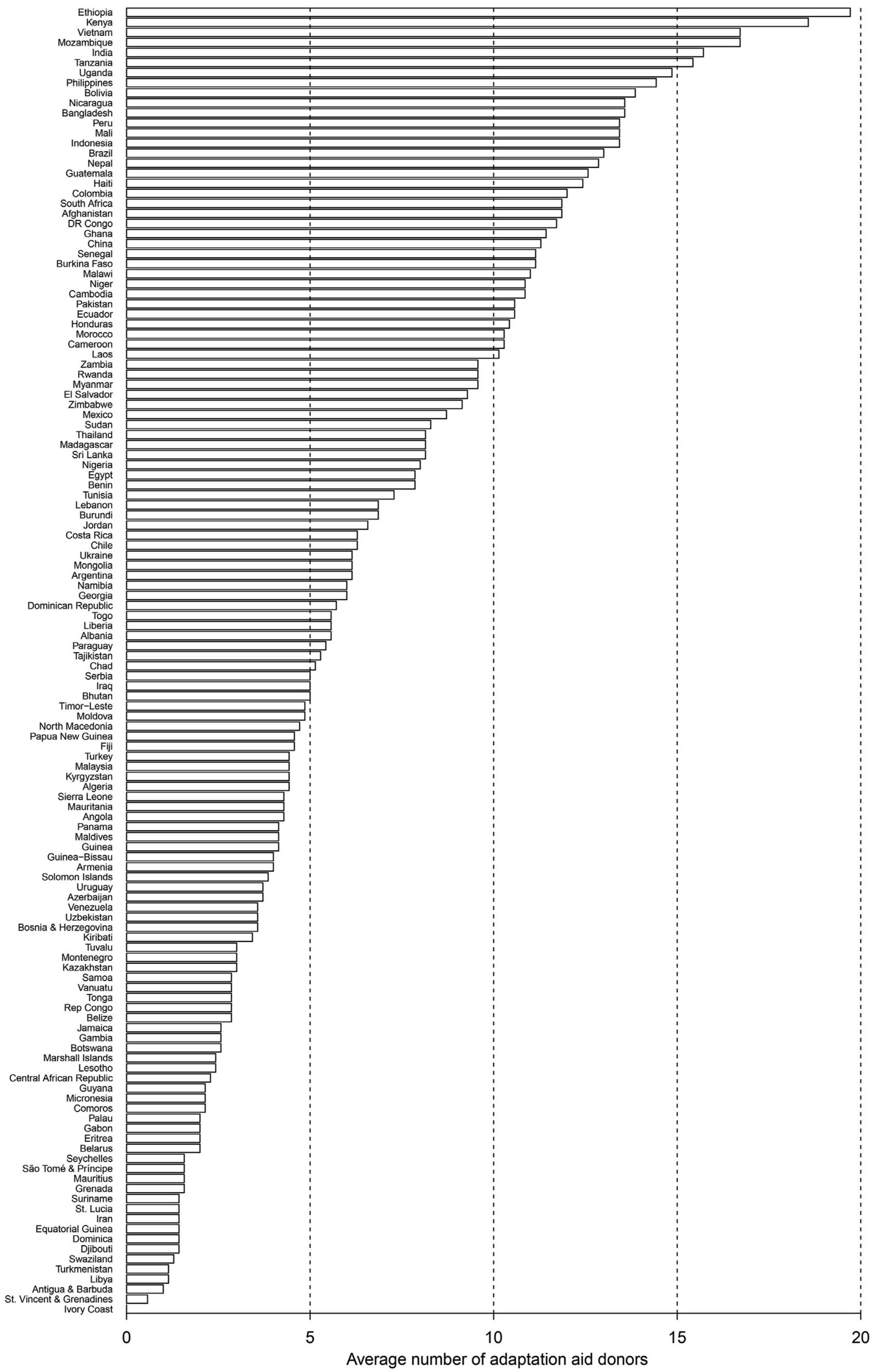

Fig. 1. Average number of adaptation aid donors for each recipient country (2010–2016).

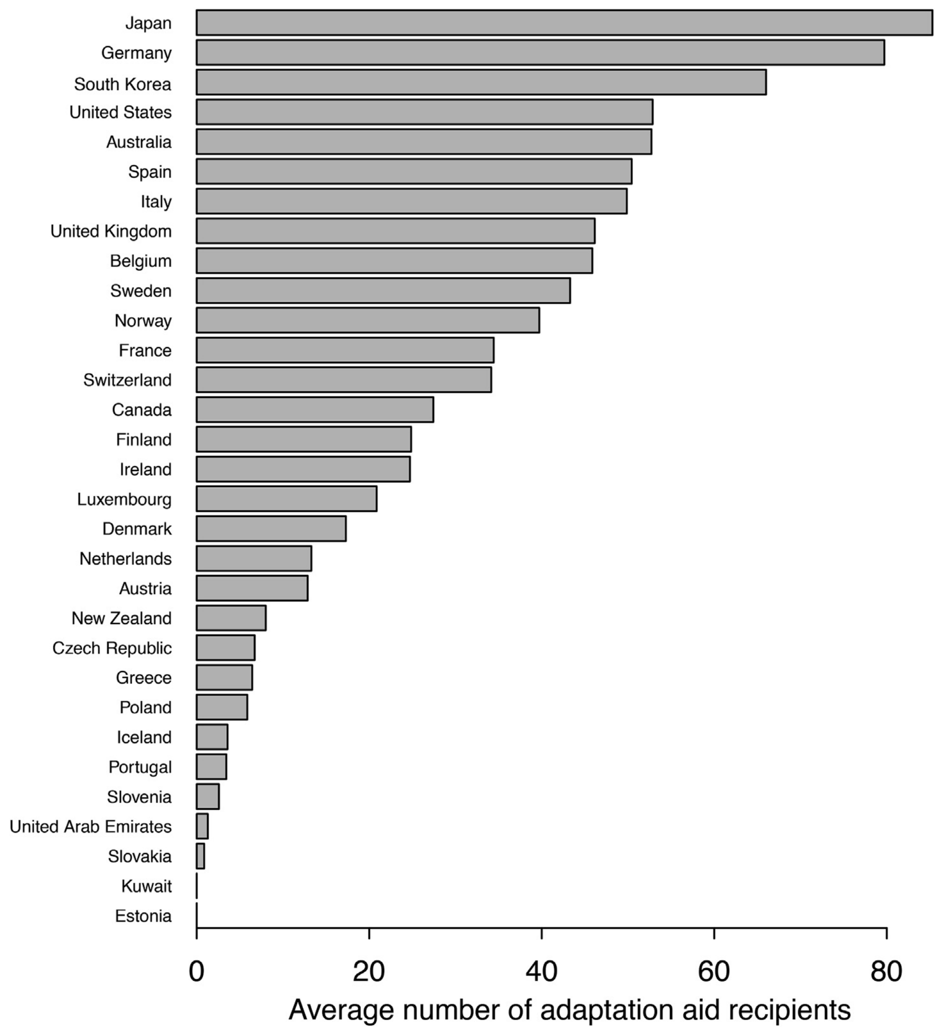

Fig. 2. Average number of adaptation aid recipients by donor (2010–2016).

Afghanistan, India, Vietnam, Mozambique, Philippines, Ethiopia and Kenya thus received adaptation aid from 21 or more different donors. In contrast, Ivory Coast, Saint Vincent and the Grenadines, Djibouti, Iran, Palau, Turkmenistan and Samoa received adaptation aid from only four different donors. Many of these are very small, so we do not expect many donors to be active there, although the network effects (discussed in the next section) do suggest that the presence of other donors matter even when we take into account population size, vulnerability, or other factors.

We can also descriptively look at adaptation aid flows from a donor perspective, as Fig. 2 does. The figure shows the average number of recipients obtaining aid from a given donor per year over the time-horizon of the study. Again, we see a large variation in the number of recipients that donors provide adaptation aid to. Some donors spread their adaptation aid relatively widely among recipients. Japan is the most prolific donor, providing adaptation aid across the seven years included in the analysis to 124 recipients (out of 130 eligible countries). Japan is followed by Germany and South Korea, with 110 and 109 recipients, respectively. Other donors, such as Slovenia, United Arab Emirates and Slovakia, focus their adaptation aid on just a few recipients, not least because their development budgets are much smaller and so only support a small number of adaptation projects. Finally, Kuwait and Estonia did not register any adaptation aid projects during the seven years of the analysis.

Overall, 16 donors provide adaptation aid to 50 or more recipients at least once. On a yearly basis, donors support adaptation in 28 recipient countries on average (see Fig. 2). When looking deeper into the adaptation aid relationships, we find that donors are indeed engaged in similar sets of recipient countries. For example for 2015, the two most active donors, Japan and Germany—who provided adaptation aid to 91 and 75 countries in 2015 respectively—had an overlap of 58 recipients to which both provide adaptation aid. While some overlap should of course be expected given that there are only 130 recipient countries in the dataset, this nevertheless means that while Germany selected a country chosen by Japan with a probability of 63.7%, this probability dropped to 43.5% for countries not selected by Japan. We find similar effects for most donor pairs, as well as in the statistical analysis, discussed below.[5]

[5] We see similar patterns among almost all country pairs. However, Japan, Australia, and South Korea all show higher probabilities of aid provisions when European and American donors are active, yet the increases in those probabilities are not as pronounced. New Zealand does not seem to follow European and American donors. However, among them these four countries follow similar allocation patterns. Thus, there seem to be two clusters of donors, one among European and North American donors, and one among Asia-Pacific donors.

Table 1
Results of the bipartite and full temporal exponential random graph models, including confidence intervals.

	Model 1 (bipartite)	Model 2 (full)
In-degree (geometrically weighted)	−0.72[a]	−0.83[a]
	[−1.21; −0.03]	[−1.31; −0.17]
Out-degree (geometrically weighted)	−5.86[a]	−6.81[a]
	[−7.31; −4.73]	[−8.39; −5.64]
Endogenous controls		
Edges	−10.02[a]	−11.18[a]
	[−13.26; −5.88]	[−13.66; −8.61]
Actor in-degree:0 (isolates)	−2.26[a]	0.58
	[−4.09; −0.63]	[−0.07; 1.49]
Actor out-degree:0 (isolates)	−0.02	0.17
	[−0.62; 0.96]	[−1.72; 1.69]
Edge memory	1.15[a]	1.15[a]
	[1.03; 1.27]	[1.02; 1.27]
Exogenous controls		
Vulnerability (ND-GAIN)	2.42[a]	2.16[a]
	[1.96; 2.90]	[1.80; 2.89]
GDP (logged)	1.61[a]	1.80[a]
	[1.76; 2.29]	[1.22; 2.33]
GDP (logged, squared)	−0.11[a]	−0.13[a]
	[−0.15; −0.06]	[−0.16; −0.10]
WGIs	0.21[a]	0.18[a]
	[0.10; 0.31]	[0.05; 0.29]
Exports from donors to recipients (logged)	0.08[a]	0.15[a]
	[0.06; 0.11]	[0.11; 0.20]
UN voting similarity	0.83[a]	0.90[a]
	[0.33; 1.58]	[0.36, 1.70]
Former colonial status	0.21	0.08
	[−0.17; 0.60]	[−0.32; 0.43]
Total development aid (logged)	0.51[a]	0.50[a]
	[0.43; 0.60]	[0.42; 0.58]
Population (logged)	0.04[a]	0.02
	[0.02; 0.08]	[−0.01; 0.06]
Africa dummy	−0.12[a]	−0.17[a]
	[−0.27; −0.01]	[−0.30; −0.04]
LDCs dummy	−0.06	−0.09[a]
	[−0.16; 0.04]	[−0.16; −0,03]
SIDS dummy	−0.07	0.14[a]
	[−0.20; 0.02]	[0.04; 0.25]
Annex 1 dummy		−1.57[a]
		[−1.85; −1.32]
Number of actors	(161)	161
Number of donors	31	(31)
Number of recipients	130	(130)
Number of dyads (per year)	4030	25760
Number of edges (average across years)	865	865
AUC precision-recall	0.76	0.77

[a] Significant at 5% confidence level; AUC = area under the curve.

4.2. Network effects

The descriptive results in Figs. 1 and 2 suggest some extent of donor proliferation for the case of adaptation aid, that is, a number of recipient countries receive adaptation aid from many donors at once. Let us now turn to a more systematic test of the interactions between donors' allocation decisions. Table 1 shows the results of the two network models. Model 1 is the bipartite (two-modal) model with the *a priori* separation between donors and recipients, while Model 2 uses the full networks (including all dyads) as dependent variable and instead includes the Annex I dummy to separate the two.

While we have strong reasons to believe that adaptation aid allocation decisions are interdependent, it is *a priori* unclear whether this effect is positive or negative, that is, whether the presence of other donors increases (H1) or decreases (H2) the likelihood of an additional donor to also provide aid. Recall from the discussion above that negative coefficients for in-degree and out-degree—as reported across the models in Table 1—suggest a positive effect: recipients are *more* likely to receive adaptation aid from additional donors the more donors already support adaptation (in network terminology: as their in-degree increases). Similarly, donors are *more* likely to support adaptation in additional recipients the more recipients they already assist with adaptation (in network terminology: as their out-degree increases). The results of both the bipartite and full models clearly indicate that adaptation aid decisions are interdependent. The negative effect of the in-degree coefficients suggests a concentration on specific recipients. Put differently, donors seem to focus their adaptation aid on a certain subset of recipients in which other donors are already active. According to the models, with every formed tie, the probability of another donor giving adaptation aid to that particular recipient country increases, as the coefficients are substantial and significant. In addition, the negative effect for out-degree indicates that the probability of donor countries giving adaptation aid to additional recipients increases the more ties they have already formed. Even when we take into account population size, vulnerability, or other factors, the statistical findings confirm that other donors' adaptation aid allocations to a recipient have a *positive* impact on a donor's decision to invest in adaptation in that recipient. We therefore reject H2 and instead conclude that adaptation aid is concentrated in some recipients.

Finally, we also find that the memory term in both models is positive and highly significant. This indicates that the seven aid networks in the model are highly related to each other and the aid edges remain relatively stable over time. This finding, in combination with the strong and significant effect of total development aid, shows that adaptation aid allocation decisions are highly dependent on donors' aid allocation history. Donors are very likely to provide adaptation aid to partner countries in which they have already implemented adaptation and development projects in the past. Adaptation allocation decisions are therefore—to a degree—locked in.

4.3. Other explanatory variables

Before concluding, let us briefly discuss our control variables, that is, other potential predictors of adaptation aid allocation. Here, the results are in line with other studies of adaptation aid allocation (Betzold and Weiler, 2017; Chen et al., 2018; Robertsen et al., 2015; Robinson and Dornan, 2017; Saunders, 2019; Weiler et al., 2018) and of development aid allocation more generally (Alesina and Dollar, 2000; Clist, 2011; Hoeffler and Outram, 2011). First, the ND-GAIN vulnerability score is significant and has a positive coefficient in both models. As vulnerability increases, so does the probability of tie formation for recipient countries. More specifically, the coefficient of the variable for the bipartite model is 2.42, which means that a change from the lowest observed value of physical exposure to the highest (a difference of about 0.41 in the dataset) corresponds to an increase of 163% in the probability of receiving adaptation aid from any of the donors.[6] In addition, both per capita GDP variables are statistically significant in both models, but the relationship to GDP per capita is non-linear, as indicated by the relatively large positive coefficient for GDP per capita (in the bipartite model) and the substantial negative coefficient for the squared term. In other words, very poor countries are *less* likely to receive adaptation aid than poor countries: as income increases, so does the likelihood of adaptation aid. Yet, after a threshold of around US$1400 per capita, the relationship changes and becomes negative: as income increases, the likelihood of adaptation aid decreases. We also find a positive and significant effect for the WGI; better governed countries are more likely to receive adaptation aid. The two variables of donor interests, UN voting similarity and exports from donors to recipients, also have positive and statistically significant coefficients. Donors thus consider their own political and economic interests when allocating adaptation aid. In contrast, we do not find that colonial ties influence adaptation aid allocations.

These findings for the control variables, which are consistent with the literature, are a first indication of the goodness of fit of the models. To further test this goodness of fit, we draw 500 simulations for the aid networks from the model, and compare several network characteristics of the simulations to the original networks. The results, depicted in Fig. 3 for Model 1, demonstrate that the models capture network properties very well, as the simulations drawn from the model (the grey boxplots) closely resemble the original networks (the black lines). This indicates that the dependency structures in the original networks have been captured well, and means that the danger of omitted variable bias due to missing variables can largely be ruled out (Cranmer et al., 2017). In addition, the precision-recall (PR) and receiver-operating characteristic (ROC) curves, shown in Fig. 4 (again for the bipartite model), both indicate that the model does a better job when predicting network ties than a null model. ROC and PR are alternative measures to capture whether a model is able to reproduce network ties correctly (Leifeld et al., 2018). PR curves close to the upper-right corner indicate a good predictive performance, while ROC curves pointing to well-performing models trend towards the upper-left corner. This is clearly the case for all the annual aid networks captured in Fig. 4.

5. Conclusion

Industrialised countries have a moral as much as a legal obligation to assist vulnerable developing countries deal with the adverse effects of climate change. While more and more development aid targets climate change adaptation, it is unclear how that aid is allocated. We here argued that these allocation decisions are influenced by donor—donor interactions, alongside recipient characteristics, donor characteristics and donor-recipient relationships that the literature has already examined. In other words, we posited that donors do not make allocation decisions in isolation but take into account the allocation decisions of their peers. By modelling adaptation aid allocation as a network, we could directly assess such interactions, and found strong evidence for donor concentration: Donors are much more likely to support adaptation in a recipient country in which other donors do so, too. This means that donors tend to support adaptation in similar sets of recipient countries, as the general development literature also suggests (Barthel et al., 2014; Fuchs et al., 2015; Olivié and Pérez, 2016; Swiss, 2017).

Clearly, our analysis is limited by the modelling technique we use. TERGMs are relatively new models that can only handle dichotomous variable; we are thus unable to also assess whether the *amount* of adaptation aid *i* allocates to *r* varies systematically with the amount of adaptation aid other donors allocate to *r*. We are also unable to examine the reasons for donors to assist similar recipients in adaptation, nor the effects of this focus on some recipients. We also do not know *why* donors provide adaptation aid to similar recipients; do other donors' allocation decisions serve as signals of vulnerability or adaptation "readiness", or do donors compete for influence in the same recipient countries? Are some recipients better able to attract adaptation investments, e.g. because they have clear adaptation priorities and plans? More qualitative research is better placed to address these important questions, and our analysis could guide such research and for example point to countries in which in-depth case studies would be particularly fruitful.

While some may contend that a focus on the same set of countries is not problematic but enables synergies and collaboration among donors, it seems more likely that adaptation aid concentration decreases aid effectiveness, as suggested by the wider development literature. Moreover, adaptation aid concentration is probably also problematic because of the well-documented adaptation finance gap (UNEP, 2021): as there is by far too little finance to meet adaptation needs in developing countries, donors should presumably focus their efforts on a variety of recipient countries rather than assisting those that other donors already help with climate change adaptation. Overall, rather than providing new and additional resources to all developing countries in need, it seems that donors mostly reproduce development aid structures and processes (Scoville-Simonds, 2016). While a direct comparison of climate and development aid is beyond the scope of this article, this observation that the former reproduces the patterns of the latter is corroborated by comparable results in the general aid literature,

[6] To obtain this result, we calculate (exp(2.42)^.4-1)*100=163.27. In the first step, the log-odds are transformed into the odds ratio, from which then the percentage change can be calculated.

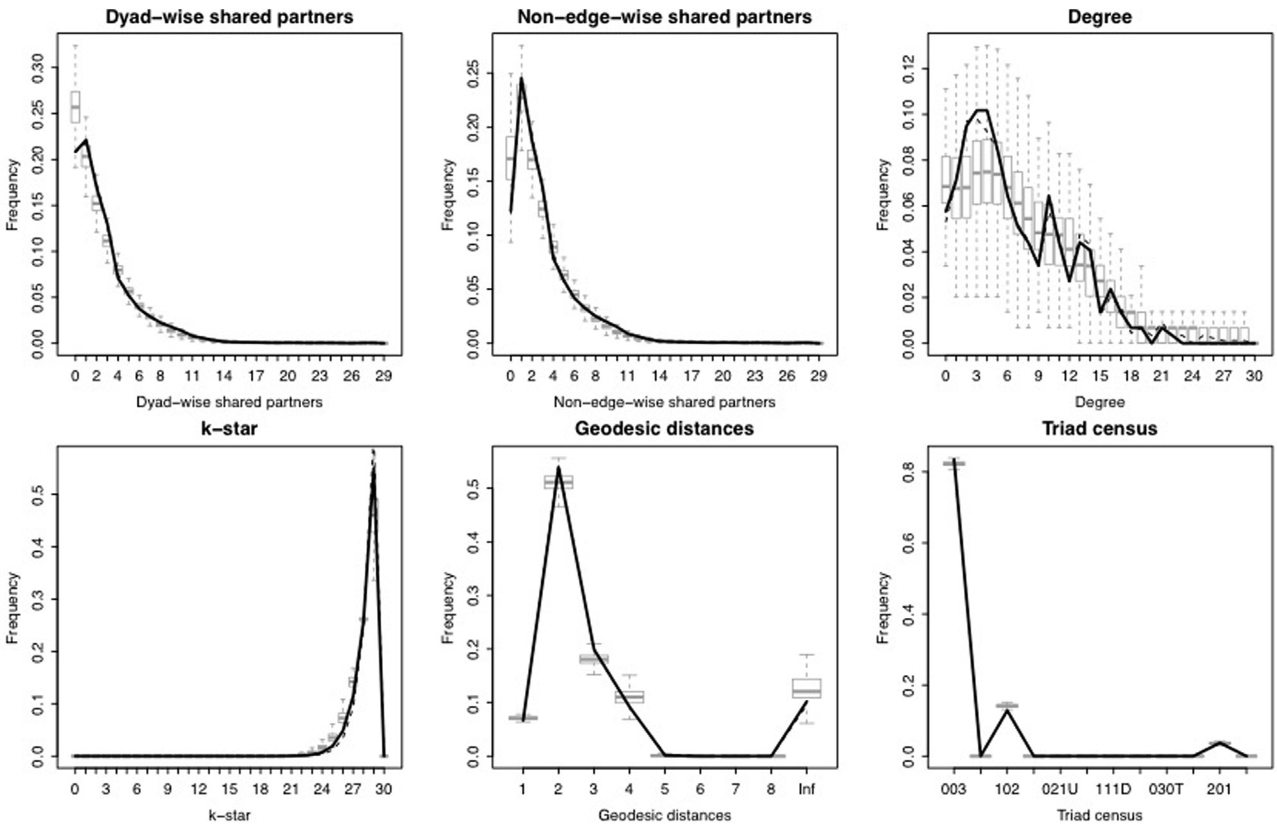

Fig. 3. Endogenous goodness of fit diagnostics for Model 1 of Table 1.

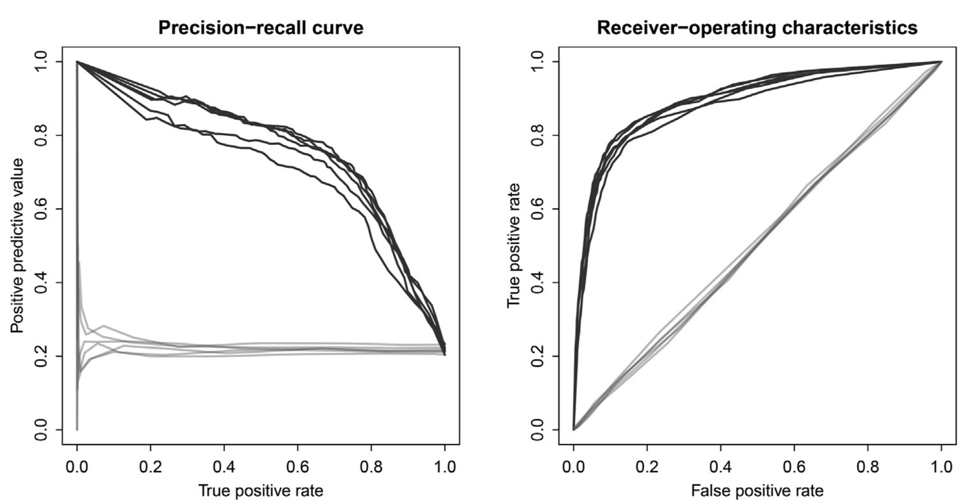

Fig. 4. PR and ROC curves for the various aid networks, with the light-shaded curves serving as the null models to allow model comparison.

which finds a similar level of aid concentration, with donors dividing recipients into aid ‘darlings’ and ‘orphans’ (Davies and Klasen, 2019). Looking at this empirical evidence through the prism of climate justice, it could be argued that donors do not fulfil their promises and pledges.

CRediT authorship contribution statement

Florian Weiler: Conceptualization, Methodology, Data curation, Modelling, Writing, Submission and Resubmission. **Carola Klöck:** Conceptualization, Theory development, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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