# Allocation of Adaptation Aid: A Network Analysis

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**Abstract**

In the run-up to Paris, individual countries and multilateral banks made new promises to provide millions of dollars for adaptation (and mitigation) action in developing countries, with a view to reaching the USD 100 billion target announced in Copenhagen and confirmed in Paris. But where are all these funds going to? To what extent do they reach the poorest and most vulnerable, those most in need of support?

The focus of this paper is on bilateral aid for adaptation to climate change. Using OECD data on adaptation aid, we examine how donors allocate this aid—and to what extent they indeed prioritise those 'particularly' vulnerable to climate change. To understand donor behaviour, we build on the large literature on aid allocation in general, and on adaptation aid in particular. Yet, as opposed to traditional dyadic analyses, we conceptualise aid allocation as a network, in which the provision of adaptation aid is a network tie. This network approach, we argue, is better able to capture interactions between donors, for the allocation decisions of others likely influence a donor's allocation decision. Donors on the one hand coordinate their allocation, but on the other hand also compete for political and economic influence through the provision of aid, including aid for adaptation. In order to capture these coordination dynamics in addition to the dyadic relationships between donors and recipients we employ Temporal Exponential Random Graph Models.

Our analysis indicates that donors consider recipient need and recipient merit when deciding on how to allocate adaptation aid: more vulnerable and more democratic countries are more likely to receive adapation aid. More importantly, however, donors consider their own economic and political interests: trading partners and former colonies are much more likely to receive adaptation aid. Finally, we also find evidence for donor coordination: countries that already receive adaptation aid from other countries are less likely to form additional ties, that is, they are less likely to also receive adaptation aid from additional donors.

## 1 Introduction

More and more aid is earmarked for climate change mitigation and adaptation. Notably since the Copenhagen pledge of 'mobilizing jointly USD 100 billion dollars a year by 2020' (UNFCCC 2009: article 8)—a goal that was confirmed in the Paris Agreement—donors have provided increasing levels of climate-related aid. We here focus on adaptation, where public funding in the form of aid is of particular importance, and specifically examine the allocation of bilateral adaptation aid: how do donors distribute their adaptation aid among recipient countries?

There is a consensus that adaptation aid should prioritise developing countries that are 'particularly vulnerable' to the adverse effects of climate change. Already the 1992 United Nations Framework Convention on Climate Change (UNFCCC) stipulates that developed countries 'assist the developing country Parties that are particularly vulnerable to the adverse effects of climate change' (UNFCCC 1992: article 4(4)). Later agreements confirmed the focus on vulnerable countries; most recently, the Paris Agreement recognises the importance of developed country support for adaptation, and again highlights the specific needs of particularly vulnerable countries (UNFCCC 2015).

While we would therefore expect vulnerable countries receive relatively more adaptation aid, other factors likely also play a role. For general development aid, research has since the 1970s found that beyond recipient need, donors also take into account recipient merit and donor interests when allocating aid: Donors do not only altruistically assist countries most in need of support, but use development aid to reward certain recipient characteristics like good governance as well as to further their own economic, political and security interests (e.g. Clist 2011; McKinley 1978; McKinley and Little 1977; 1979; Neumayer 2003; Zanger 2000). Finally, donors likely consider the allocation decisions of other donors in their own allocation decisions. Aid flows from other donors serve as signals on the trustworthiness and efficiency of a recipient—hence the existence of 'aid orphans' and 'aid darlings'. At the same time, there is increasingly a push toward more donor coordination to increase aid effectiveness (see OECD 2008).

While we have thus strong reasons to believe that donors influence each other in their allocation decisions, 'the interaction between members of the donor community has been little studied' (Frot and Santiso 2011: 57; see also e.g. Klasen and Davies 2011). We address this gap in the literature and explicitly examine donor interactions by conceptualising aid allocation as a network, in which the provision of adaptation aid is a network tie. Through this network approach we are able to capture both 'traditional' determinants of allocation—recipient need, recipient merit and donor interests—and interaction effects between donors, and hence obtain a fuller picture of allocation patterns than we would with dyadic regression analysis.

## 2 Literature Review and Expectations

How donors distribute their development aid among recipients has received considerable academic attention. McKinley and Little (1977; 1979) and McKinley (1978) were the first to distinguish between two donor motives: recipient need and donor interest. Subsequent studies built on and extended this model by adding recipient merit as a third donor motive for allocating aid (e.g. Alesina and Dollar 2000; Burns 2000; Clist 2011; Zanger 2000). Most studies find evidence for different motives, although donor interest—political, economic and security interests of the donor(s)—tend to dominate and can much better explain allocation patterns than either recipient need or recipient merit (e.g. Alesina and Dollar 2000; Berthélemy 2006; Hoeffler and Outram 2011).

Studies that focus on 'green' aid, that is, aid with an explicit environmental dimension, find similar results: donors have different motives in allocating (green) aid, though donor interest often plays a stronger role than recipient need or recipient merit (Figaj 2010; Halimanjaya 2015; Hicks et al. 2008; Miller 2014).

Most recently, several studies specifically examined the allocation of aid for adaptation to climate change. A few studies focus on normative assessment of how adaptation aid *should* be allocated, and argue for a focus on vulnerable countries (e.g. Duus-Otterström 2015; Grasso 2010a;b)—though admitting to the difficulties of identifying which countries are vulnerable (Klein 2009). Only a few studies empirically examined the distribution of adaptation aid, for individual donors like Germany (Betzold 2015) or the multilateral Adaptation Fund (Persson and Remling 2014; Remling and Persson 2015; Stadelmann et al. 2014); for a subset of recipients such as sub-Saharan Africa (Robertsen et al. 2015) or small island developing states (Robinson and Dornan 2015); for distribution at the sub-national level within a recipient country (Barrett 2014); and for aggregate aid flows across all donors (Betzold and Weiler 2016). These empirical studies find limited evidence that vulnerable countries receive more support for adaptation. While vulnerable countries—measured by different vulnerability indicators—receive more adaptation aid on an aggregate level (Betzold and Weiler 2016), overall, recipient merit and donor interest seem better able to explain allocation patterns of adaptation aid.

These studies have neither examined dyadic data for *all* OECD donors and *all* recipients, nor have they considered network effects. This paper thus goes beyond current research by modeling the allocation of adaptation aid as a *network* between all OECD donors and all potential recipients.

In line with both the literature on general development aid and the more recent literature on 'green' and adaptation aid, we expect the 'traditional' determinants of aid allocation—recipient need, recipient merit and donor interests—to influence how donors distribute their aid for adaptation to climate change. Our first three expectations reflect this framework. Additionally, we add two specific network expectations.

Adaptation aid reportedly aims at assisting developing countries in coping with and adjusting to the adverse effects of climate change. Recipient need, in an adaptation context, therefore translates as vulnerability to climate change. The more vulnerable a country to the adverse effects of climate change, the more in need of external support to deal with these effects it is, and so donors should be more likely to provide adaptation aid to this country:

**H1** The more vulnerable a recipient country to the adverse effects of climate change, the more likely it will receive adaptation aid.

Burns (2000) introduced the argument that aid is more effective in countries with 'good', that is democratic, polities and 'good' economic and fiscal policies. By rewarding 'good governance' in recipient countries, donors could thus increase the effectiveness of their aid (see also e.g. Zanger

2000). Good governance should also matter for adaptation aid, since adaptation aid is likely to yield better results where good (environmental) policies are already in place, and can be used to reward such policies.

**H2** The better the (environmental) governance of a recipient country, the more likely it will receive adaptation aid.

Our third expectation concerns donor interests. As opposed to the first two expectations, which relate to recipient characteristics, donor interests are specific to the donor–recipient pair. Donors use their aid to further their own political, economic and security interests, by providing support to their political friends, trade partners or military allies (e.g. Hoeffler and Outram 2011; Neumayer 2003). This applies in particular to bilateral aid; as Berthélemy (2006: 88) writes, 'bilateral aid motives are, to a large extent, egoistic rather than altruistic'.

'Green' aid and adaptation aid is no exception: donors also use their environmental aid to further their own interests (e.g. Barrett 2014; Betzold 2015; Hicks et al. 2008), as our third expectation reflects:

**H3** The more important a recipient country to a donor—economically or politically—the more likely it will receive adaptation aid from this donor.

Finally, we also have two (opposing) expectations concerning the *network* of donors. We believe that donors do not take their allocation decisions independently of the decisions of other donors, though these interactions between donors have rarely been studied: 'there exists remarkably little analysis on how in actual fact aid allocation to particular countries is affected by aid flows from other donors' (Klasen and Davies 2011: 5; see also Davies and Klasen 2013; Frot and Santiso 2011).

So how do aid flows from other donors affect the allocation decision of a donor? On the one hand, we expect a negative relationship between a recipient's in-degree and the likelihood of new ties: the higher the number of donors providing adaptation aid to a recipient country $R$, the lower the likelihood of an additional donor to also provide adaptation aid to $R$, for different theoretical reasons.

First, donors should have an interest in collectively maximising the impact of their aid. The tendency of donors to provide aid 'to all sectors in all countries' causes severe administrative costs (Easterly 2007: 639f). According to Bigsten and Tengstam (2015), the average donor has over 100 partner countries and regions; by focusing on fewer countries, donors could realise significant cost savings and efficiency gains (see also Nunnenkamp et al. 2013). Accordingly, in the 2005 Paris Declaration on aid effectiveness and follow-up agreements, donors agreed on greater donor coordination to improve aid efficiency and aid effectiveness, and committed to eliminating duplication of efforts and concentrating their aid on fewer countries (OECD 2008).

Similarly, if aid is about gaining political influence in the recipient country, and if donors want to maximise their influence, then it may make sense to focus aid on those countries where other donors are not active. According to this logic, if recipient $R$ already obtains aid from donor $A$, donor $B$ has to compete with $A$ for influence in country $R$; instead, $B$ may simply to turn to recipient $S$, where $A$ is not active, and where $B$'s aid will hence have a greater impact (cf. Bunte and Kinne 2015).

Finally, Chong and Gradstein (2008) put forward a 'freerider hypothesis': If aid is about relieving recipients' need—be that poverty or vulnerability to climate change, donors can free-ride on the efforts of others. Accordingly, their study finds that each donor provides less aid as the number of donors increases.

In line with these theoretical considerations, our first network hypothesis expects a *negative* relationship of a country's in-degree and its likelihood of receiving additional adaptation aid:

**H4** As a recipient country's in-degree increases, its probability of receiving additional adaptation aid decreases.

In practice, however, we see much rhetoric but few deeds; aid fragmentation persists (e.g. Olivié and Pérez 2016: 52; Aldasoro et al. 2010), and may even have increased since the Paris Declaration Nunnenkamp et al. (2013).[1] Donors tend to herd (Frot and Santiso 2011): they provide aid to those countries which already receive aid from other donors (e.g. Barthel; Dreher and Michaelowa 2010). The opposite seems also true; accordingly, we have so-called 'aid darlings' and 'aid orphans': countries that receive fairly high—or fairly low—levels of support across donors.

Donors take into account the behaviour of other donors, and a donor's giving aid to a specific recipient provides important information about that recipient to other donors, including the recipient's absorptive capacity or its political or economic relevance. Donor $A$'s provision of aid to recipient $R$ signals to donor $B$ that recipient $R$ seems trustworthy and capable of using the provided aid efficiently and effectively, or that recipient $R$ is an important political or economic player for $A$ (see Barthel; Olivié and Pérez 2016). This should make donor $B$ more inclined to also provide aid to $R$. The opposite also applies: If donor $A$ does not provide aid to recipient $R$, donor $B$ should also be reluctant to become active in recipient $R$ .

In the case of adaptation aid, if recipient $R$ receives adaptation aid from donor $A$, $R$'s adaptation 'readiness' is presumably high, for instance because it has already made national adaptation plans and strategies, and can thus directly implement adaptation actions. Accordingly, our second network hypothesis expects a *positive* relationship between a country's in-degree and its likelihood of receiving additional adaptation aid:

**H5** As a recipient country's in-degree increases, its probability of receiving additional adaptation aid increases.

[1] In contrast, Davies and Klasen (2013) find a positive time trend, indicating growing aid coordination and specialisation.

# 3 Data and Methods

Our basic dependent variable consists of five annual network capturing donor–recipient relationships in the period 2010 through 2015. In other words, for each of the five years we have a network $\mathbf{Y}$ for which the individual dyads $Y_{ij}$ take on the value 1 when government $i$ made adaptation aid available to country $j$, and zero otherwise. Thus, we have five dichotomous networks for the years 2010 through 2014. The data used to code the networks come from the Organisation of Economic Cooperation and Development Creditor Reporting System (OECD CRS). The OECD introduced a 'Rio marker for adaptation' in 2010, according to which any activity should be classified 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: 4). Consequently, if in the CRS a country reports to have provided adaptation aid to a recipient country in a given year, this is recorded in the respective network as a tie.

The data structure we have is problematic from a statistical point of view, since the different networks for the various years are very likely not independent of each other, as are the dyads (see hypotheses 4 and 5, which expect the allocation decisions of donors to depend on the decisions of others). One way to model such a data structure are Temporal Exponential Random Graph Models (TERGM), which can capture both the network dynamic in a given year and cross-temporal correlations.

How do we measure our independent variables? Recipient need, in the case of adaptation aid, refers to vulnerability to climate change. Vulnerability is a contested concept with no single definition, though most scholars agree that vulnerability has two dimensions: physical exposure and sensitivity to natural hazard on the one hand, and adaptive capacity on the other (e.g. Barnett et al. 2008; Smit and Wandel 2006). To capture these two dimensions of vulnerability, we use three different indicators.

First, we use the environmental vulnerability index, EVI. The Secretariat of the Pacific Community's Applied Geoscience and Technology Division (SOPAC) produced the EVI in 2004 to 'estimat[e] the vulnerability of the environment of a country to future shocks' (SOPAC 2004). We focus on the EVI Climate Change Subindex, an average of thirteen climate-related geo-physical indicators such as precipitation patterns. It is time-invariant and ranges from 1 to 7, where higher scores indicate higher vulnerability (for a detailed description, see Kaly et al. 2004).

Second, we use the University of Notre-Dame's Global Adaptation Indicator, ND-GAIN. The ND-GAIN takes into account vulnerability—understood as including the three components of exposure, sensitivity, and adaptive capacity—as well as readiness, the 'ability of a country's private and public sectors to absorb financial resources and mobilize them efficiently to reduce climate change vulnerability' (ND-GAIN 2013: 2). We use the vulnerability sub-index, that is, we exclude readiness as we want to control for income separately. The vulnerability sub-index score is composed of 36 indicators and scaled to range from 0 to 1, with higher values indicating higher levels of vulnerability (see ND-GAIN 2013; nd).

Finally, as an—admittedly—rough proxy for adaptive capacity, we include gross domestic product GDP per capita. Adaptive capacity is hard to measure, as it depends on many factors, including information, education, social cohesion, technology, and resources. We here focus on GDP per capita since many of the factors such as education or technology tend to correlate with GDP per capita and since data is readily available. We use annual data from the World Bank's World Development Indicators (World Bank 2014).

To test for recipient merit, that is good (environmental) governance, we include two measures: the imputed Polity 2 scores from Freedom House on the one hand, and control of corruption from the Worldwide Governance Indicators. Although more specific environmental policy indicators would be a better proxy, there is a lack of data on such policies. Democracies, however, often have a better environmental track records (e.g. Bättig and Bernauer 2009), and so we first use the imputed Polity 2 variable, which measures countries' level of democracy on a scale from 0 to 10, where 0 is least democratic and 10, most democratic. We prefer this measure over the original Polity 2 score as it has the widest coverage spatially and temporally.[2] Data is annual and comes from Teorell et al. (2015). We further include a measure of corruption, as lower levels of corruption are a good indicator for the capacity of countries to make good use of funds provided by donors. The variable control of corruption is part of the Worldwide Governance Indicators (Kaufmann et al. 2014), and is, by design, standardised. Accordingly, the variable ranges from about -2.5 to +2.5 around a mean of zero with a standard deviation of 1.

We have three commonly used measures to capture donor interests: trade as a measure of economic interests; joint voting in the United Nations General Assembly as a measure of political interests; and colonial past as a measure of historical relations.

First, trade data is taken from the UN Comtrade Database (United Nations Statistics Division 2015). For each of the five years in our dataset (2010 through 2014), we construct a trade network which captures how much each of the country pairs traded in a given year. For each country pair, both parties report their exports and imports. Thus, the exports reported by country $A$ to country $B$ should equal the imports reported by country $B$ from country $A$. Often, however, there are discrepancies between these reported data. We therefore decided to use in such cases the higher value, since underreporting (or not reporting any trade) seems a problem particularly in smaller and poorer countries. The final network in a given year then consists of the sum of the thus adjusted import plus export values. This final value is then logged.

Second, Strezhnev and Voeten (2013a) collect data on voting patterns in United Nations General Assembly roll-call votes. Specifically, they calculate a Voting similarity index (Strezhnev and Voeten 2013b), which captures how often each country pair agrees when they vote 'yes' (approve), 'no' (disapprove), or abstain (with abstention also being counted as half-agreements with both yes and no votes). This count is then standardised to range from zero (no agreement on any issues) to one (full agreement on all issues).

Finally, the analysis includes a network capturing colonial ties. This network of the same 167 countries as in the aid network simply takes on the value of one if the two countries share a

[2]The Polity 2 score are not available for small countries with less than 500,000 inhabitants.

colonial past, that is, if one country has ever been a colony or coloniser of the other country, otherwise the value is set to zero. There are nine different colonial powers in the dataset, and 113 colonial ties.

Additionally, the analysis includes a memory term, that is whether network ties from previous periods influence network formation in later years. We also control for a country's overall GDP as a general measure for the size and importance of the country. Data are from the World Bank (2014).

## 4 Results

| | Partial Model 1 | Partial Model 2 | Full Model |
|---|---|---|---|
| Indegree | $-2.56^*$ | $-2.57^*$ | $-2.54^*$ |
| | [−2.79; −2.13] | [−2.81; −2.18] | [−2.75; −2.25] |
| Outdegree | $-8.48^*$ | $-8.46^*$ | $-8.47^*$ |
| | [−10.38; −7.18] | [−9.60; −7.40] | [−9.62; −7.17] |
| Vulnerab. (ND-GAIN) | $0.31^*$ | | $0.37^*$ |
| | [0.01; 0.64] | | [0.14; 0.60] |
| Vulnerab. (EVI) | | −0.01 | −0.03 |
| | | [−0.11; 0.03] | [−0.12; 0.02] |
| GDP per capita (log) | $-0.15^*$ | $-0.14^*$ | $-0.14^*$ |
| | [−0.31; −0.11] | [−0.24; −0.04] | [−0.22; −0.06] |
| FH index | $0.01^*$ | | $0.02^*$ |
| | [0.00; 0.04] | | [0.01; 0.05] |
| Control of corrupt. | | −0.02 | −0.05 |
| | | [−0.14; 0.05] | [−0.16; 0.01] |
| Trade ties (matrix) | $0.12^*$ | $0.11^*$ | $0.12^*$ |
| | [0.10; 0.14] | [0.09; 0.13] | [0.10; 0.13] |
| UN voting (matrix) | 0.49 | 0.52 | 0.51 |
| | [−0.54; 1.70] | [−0.59; 1.88] | [−0.22; 1.48] |
| Colon. ties (matrix) | $0.79^*$ | $0.80^*$ | $0.79^*$ |
| | [0.35; 1.18] | [0.38; 1.13] | [0.41; 1.18] |
| Netw. memory term | $1.20^*$ | $1.21^*$ | $1.20^*$ |
| | [1.09; 1.38] | [1.04; 1.39] | [1.11; 1.37] |
| Annex 1 dummy | $-1.25^*$ | $-1.23^*$ | $-1.24^*$ |
| | [−1.87; −0.42] | [−1.82; −0.63] | [−1.85; −0.43] |
| Total GDP (log) | 0.04 | $0.09^*$ | 0.02 |
| | [−0.01; 0.09] | [0.02; 0.18] | [−0.03; 0.08] |
| Total GDP sq. | $-0.00^*$ | $-0.00^*$ | −0.00 |
| | [−0.00; −0.00] | [−0.01; −0.00] | [−0.00; 0.00] |
| Observations | 103808 | 103808 | 103808 |

$^*$ significant at 5% confidence level

Table 1: Temporal Exponential Random Graph Models including bootstrapped 95% confidence intervals

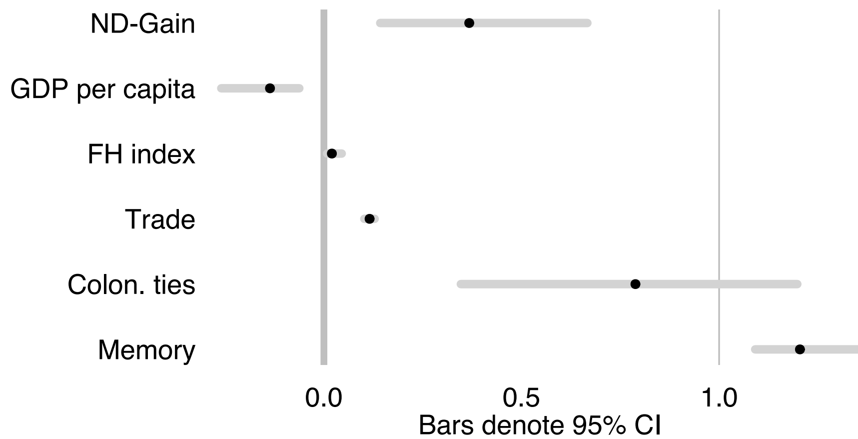

Figure 1: Significant results of full model

In this section we describe the results of the TERGMs used to model the data. Specifically, the models use the pseudo-likelihood estimation technique described in (Cranmer and Desmarais 2011; Desmarais and Cranmer 2012; Leifeld et al. 2016), and the confidence intervals are generated using 1000 bootstrapping iterations. The models we will discuss in this section are shown in Table 1. The first two models are partial models and include only a single coefficient for vulnerability to climate change impact and for the quality of government. Model 3 is a full model and contains all the variables described in the previous section. Figure 1 depicts the substantive effects for hypothesis 1 to 3 graphically. [3]

**Vulnerability:** We divide vulnerability to climate change impacts into two parts. One the one hand, it is a purely naturalistic assessment of how exposed and sensitive to climate change the various countries in the dataset are (captured by the ND-GAIN vulnerability sub-index, and the EVI climate sub-index). On the other hand, we also consider the adaptive capacity of countries as measured by per capita GDP.

The results for the ND-GAIN vulnerability index show that donor countries seem to consider the exposure and sensitivity of recipient countries when they decide who gets adaptation aid. The variable is significant and has the expected positive coefficient in both models which include this variable (columns 1 and 3 in Table 1). This means that a higher degree of vulnerability increases the chances of tie formation for recipient countries, and thus of adaptation aid from developed country governments. More specifically, the coefficient of the variable for the full model is 0.37. This implies that a change from the lowest possible value of vulnerability to the highest (a

[3]The effects for the indegree and outdegree coefficients used to test hypotheses 4 and 5 are not shown here, because the magnitude of these two effects is much larger. They are thus on a very different scale, which makes plotting them onto the same figure as the other effects difficult, as the confidence intervals of these other effects become very small.

difference of about 1 in the dataset) implies an about 45% higher chance of receiving funds from any of the donor countries.[4] This seems like a rather large effect, but it should not be forgotten that the baseline probability of forming a tie is relatively low.

The effect for the EVI climate sub-index, on the other hand, is not significant in the models reported in Table 1. Even when we do not include the ND-GAIN variable, higher EVI values do not seem to increase the likelihood of tie formation for developing countries: countries that are more exposed to climate change as measured by the EVI are not more likely to receive adaptation aid. One reason for this result might be that this index is relatively old (from 2004), and has only been calculated at a single point in time. Policy makers might no longer take notice of such an index, whose visibility decreases over the years.

Adaptive capacity, as measured by a country's per capita GDP, is significant and exhibits a negative coefficient in all models. Thus, the higher the (logged) per capita GDP, the lower the probability that developing countries forma tie with donors and receive adaptation aid. The negative coefficient of -0.14 in the full models means that when the logged GDP per capita value increases by one point, the likelihood of forming a tie decreases by about 14%. For a change from the lowest to the highest per capita GDP value among the recipient countries in the dataset, this translate to an approximately 65% reduced probability of receiving adaptation aid. This might not seem all that much, but it means that, inversely, the poorest developing countries are about 186% more likely to receive adaptation aid than the richest developing countries in the dataset. Overall, despite the insignificant findings for the EVI climate sub-index, we therefore conclude that vulnerability matters, as H1 expected: more vulnerable countries are indeed more likely to receive adaptation aid.

**Recipient merits:** To measure recipient merit, we employed both the Freedom House Polity 2 variable, and the Control of Corruption variable provided by the Worldwide Governance Indicators. As can be seen in the models in Table 1, the Freedom House index measuring the level of democracy has a positive and significant effect in both models that include this variable (columns 1 and 3). Yet the effect is relatively small: when the index improves by one point, all else equal, the models predict the likelihood to receive adaptation aid to increase only by about 2%. Therefore, the maximum effect that this variable can have is an increase in the chance of receiving aid by approximately 25%, when the Freedom Index changes from the lowest to the highest value, all else equal. Democratic performance consequently plays a role, but it seems to be less important than vulnerability to climate change impacts (both climate sensitivity and adaptive capacity) for the aid allocation decisions of donors.

Control of corruption, on the other hand, does not significantly influence how donor countries distribute adaptation aid. The coefficient for this variable remains insignificant even when we exclude the other meausre of recipient merit, that is, level of democracy (column 2 in Table 1). It is unclear why control of corruption does not seem to affect whether a country receives adaptation aid. To conclude, then, we find only limited evidence in favour of our expectation that donors

[4]To obtain this result, we calculate $(exp(0.37) - 1) * 100 = 44.77$. In the first step, the log-odds are transformed into the odds ratio, from which then the percentage can be calculated.

use adaptation aid to reward good governance (H2). The evidence is relatively weak and the predicted effect, according to the models, relatively small.

**Donor interests:** To what degree do donor interests play a role for adaptation aid allocation? We measure donor interest using three variables: trade relations, UN voting patterns, and colonial ties. While the other independent variables used so far for hypotheses testing are monadic, that is, only the characteristics of the recipient countries play a role (how vulnerable are they, how democratic are they, etc.), these donor interest variables are dyadic by definition. In other words, the characteristic of the donor itself plays a role for aid allocation decisions. For TERGMs such variables are themselves constructed as networks (using the same countries as the nodes), with the edges of the networks registering the value of the independent variable in question, i.e. the trade volume between country $A$ and $B$, or whether colonial ties between the two exist, or the similarity in their voting patterns in the UN General Assembly. These annual (in the case of the trade and UN voting data) or single networks (colonial ties) can then be included as independent variables in the TERGMs, with positive coefficients denoting that an increase in the variable in question improves the odds of tie formation, and decreases the chances of forming a tie when the effect is negative.

The annual trade networks exhibit a strong positive coefficient, indicating that a more intensive trade relationship between two countries greatly improves the chance of tie formation, and thus of recipient countries receiving adaptation aid from their trading partners. When the (logged) bilateral trade balance between a donor and a recipient increases by one unit, the predicted probability of forming a tie increases by approximately 12%. This is not an indication that larger countries, with which donors tend to trade more extensively, simply get more aid, since we control for total GDP in the models. It might well be that tie formation with larger countries is more likely (although the models are rather inconclusive on that issue), yet keeping total GDP constant, the models predict that the trade balance (strongly) influences whether developing countries receive adaptation aid, or whether they are overlooked. For instance, if the (logged) dyadic trade variable between two countries increases by 15 units, the models predict the odds of tie formation to increase be more than 450%. Again, we have to keep in mind that the baseline probability of tie formation in the aid networks is very low, only about 2.5%. Thus, even a strong growth in trade between two countries (starting at zero trade) would increase this probability of tie formation only to about 11.6%. Still, this is by far the strongest effect for all the independent variables in the models.

The UN voting networks, on the other hand, are not significant. Although they exhibit a relatively large positive effect, as expected, the coefficient has a very wide confidence interval. Thus, similar interests in international relations do not seem to translate into tie formation: recipient countries that vote in line with a donor are not more likely to receive adaptation aid from that donor.

Finally, the strong positive effect of the colonial ties network indicated that recipient countries do receive preferential treatment by their former colonial powers. All else equal, the models predict that former colonies are about 120% more likely to receive adaptation aid than developing countries without colonial ties. Thus, combining the colonial effect with the findings for the trade networks, this paper corroborates the findings of the general aid literature that donor interests are the strongest predictor for aid allocation, although donor needs (vulnerability) and donor merits (democracy) also play a role for these allocation decisions.

**Donor coordination:** Finally, we also test our expectations that a recipients' in-degree influences the likelihood of other donors giving to that country (H4 and H5). In other words, here we test whether a developing countries' nodal degree, i.e. the number of already existing links to donors, increases or decreases the odds of other donors also providing adaptation aid to that recipient country. Thus, we test if there is some form of donor coordination in the aid network, or whether the donors make their decision to form ties with recipient countries independent of each other. A positive effect would indicate that donors 'follow' where other donors are going, i.e. that they give aid to the same recipients (H5). In contrast, a negative effect is an indication that donors divide the field of recipient countries up among them, and focus more on these few countries. Thus, when a country receives aid but some donors, the likelihood of forming additional ties decreases (H4).

The negative in-degree coefficient is evidence in favour of H4: donors seem to focus their adaptation aid on a certain subset of countries, mostly countries in which not too many other donor countries are active. Indeed, according to the models, with every formed tie the likelihood of other donors giving to that particular recipient country decreases dramatically, as the coefficient is quite substantial (-2.54). In addition, the negative out-degree effect indicates that the odds of donor countries giving aid to additional recipients decrease the more ties they have already formed. Overall, this is clear evidence in favour of H4, that is, donor coordination, while H5 must be rejected.

# 5 Model fit

In this section, we briefly evaluate how well the models (particularly Model 3) fit the data. First of all, we check for model degeneracy by simulating 1,000 networks from the model. These networks are then compared to the observed networks at each observed time step. If the global statistics of the simulated networks are very different from those of the observed networks, that is, if the hypotheses that these statistics are the same are refuted (small p-values), this indicates model degeneracy. For our Model 3, not a single of the simulated statistics is significantly different than the corresponding statistic of the observed networks. The lowest p-value is 0.29 for the in-degree coefficient of the last time period. Almost all other coefficients across all time periods have p-values of about 0.5 or larger. Thus, none of our simulated coefficients is even close to a level where we observe large differences between the simulated and the observed networks. We therefore conclude that degeneracy is not a problem in our models.

Figure 2 shows the goodness of fit for Model 3 graphically. The solid black line shows the value of a certain statistic (at specifies values) for the observed networks, while the grey boxplots show the

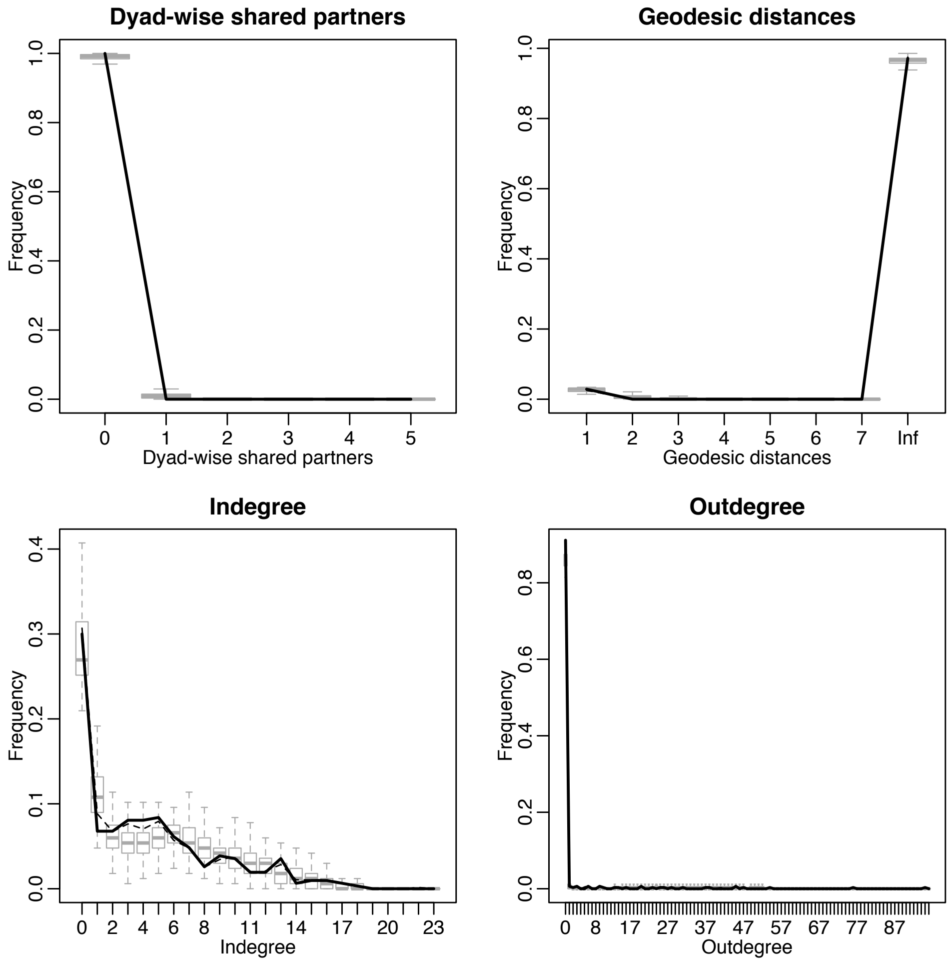

Figure 2: Goodness of fit for Model 3

predictions for the same statistic for the 1,000 simulations. We can clearly see that the predictions for the four selected network characteristics closely follow those of the observed networks, which is another indicator for the high goodness of fit of the model.

Finally, Figure 3 shows the precision-recall curve (PR) and the receiver–operating characteristics. The precision rate is an indication of the number of ties predicted for the various years that are indeed observed in the original networks. The dark blue lines show the PR curves for the annual networks, while the lighter blue lines show the curves for randomly chosen networks with the same number of ties. The further to the upper-right corner the PR curves point, the higher the precision. Clearly, the models reported in this paper have a high precision and are thus able to capture the characteristics of the original networks well. Similarly, the receiver–operating characteristics curves compare the true positives to the false positives, i.e. how often the model predicts a tie correctly, and how often the prediction of tie formation is false. Again, the curve indicates that the instances of false positives is low, and the model is well suited for capturing the characteristics of the original aid networks. Overall, we therefore conclude that the models in this paper are valid and well-suited to examine the data at hand.

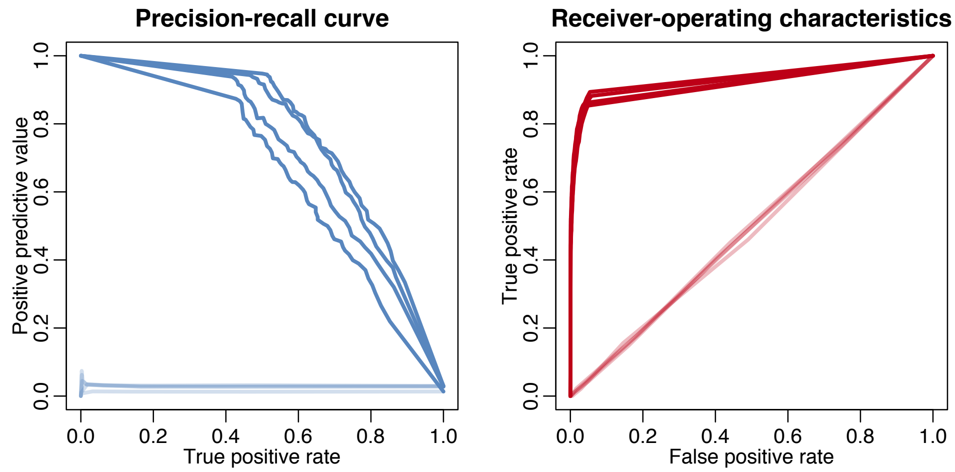

Figure 3: Precision-recall curve and receiver-operating characteristics for Model 3

# 6 Conclusion

In this paper, we examined the question how bilateral aid for adaptation to climate change is distributed. We first focused on the 'traditional' determinants of aid allocation: recipient need, recipient merit and donor interests. We understand recipient need as vulnerability to climate change in the adaptation context and used three measures: the ND-GAIN vulnerability indicator, the EVI climate sub-index and GDP per capita. We measured recipient merit as democratic status and control of corruption, and recipient interests as trade relations, UN voting patterns and colonial ties. In addition, we examined donor interaction: to what extent and how donors take into account the allocation decision of other donors when providing adaptation aid.

To answer the research questions, we employ Temporal Exponential Random Graph Models (TERGMs). Our dependent variable consists of five adaptation aid networks for the years 2010 through 2014. These networks capture whether a particular donor country provides adaptation aid to a developing country in a given year. The entries in the network matrices take on the value of one when a tie exists, and zero otherwise. Such a data structure could be modelled using traditional panel data methods. However, ¶textsctergms are particularly useful to capture network effects such as tie formation based on the allocation decisions made by others. In addition, the temporal dimension, i.e. how allocation decisions in past years influence adaptation aid distribution in later periods, can be modelled in the TERGMs used in this paper. We demonstrate that these models are clearly able to capture the particular structure of the underlying data.

Our results show that recipient need, recipient merit and also donor interests all play a role for aid allocation decisions of developed countries. However, we also see that these determinants clearly differ in their importance when donor countries decide on how to allocate adaptation aid. The most important determinant of adaptation aid allocation, according to our models and in line with previous research, is donor interest. Particularly trade relations and colonial ties both have a strong positive effect, and the size of the coefficients of these two variables show that they greatly influence the probability that a given recipient country receives aid from the donor in question.

Recipient needs, measured by vulnerability to climate change impacts on the one hand, and by adaptive capacity (measured as GDP per capita) on the other hand, also significantly influences the decision making process, although the magnitude of these effects is considerably smaller than of those for donor interests. Finally, recipient merit, particularly democratic status, also play a significant role when developed countries decide how to allocate adaptation aid. However, the magnitude of this donor merits effect pales in comparison to the other two.

Finally, we were also able to show that donors do not make their allocation decisions independently from each other, but that they consider how others distribute their aid. More specifically, when recipients already receive aid from a host of other donors, the likelihood that a donor country will also form ties with recipients decreases quite dramatically. This means that donors try to focus on a certain set of recipient countries, which is also shown by the high stability of the aid networks across time (the memory term is positive and highly significant).

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