1. Introduction

Climate aid – official development assistance (ODA) relevant for adaptation and mitigation – is on the rise. Notably since the Copenhagen goal of 'mobilizing jointly US$100[1] billion dollars a year by 2020' and of 'providing $30 billion for the period 2010–2012' (UNFCCC 2009: paragraph 8) for mitigation and adaptation in developing countries, developed countries have scaled up their climate-related aid.

So far, only a small part of this climate-related aid targets adaptation; the OECD estimates that 16% of all mobilised climate finance in 2013 and 2014 addresses adaptation (OECD 2015). But adaptation aid is growing, In the Paris agreement, for instance, Parties explicitly repeated the need to 'balance' adaptation and mitigation (UNFCCC 2015: paragraph 9). Yet, we still know surprisingly little about international adaptation aid, including how much public adaptation funds are available (both in terms of commitments and disbursements), who receives how much funding, what the funding is used for, or to what extent it effectively reduces vulnerability and increases resilience among recipients (e.g. Peterson Carvalho and Terpstra 2015: 2).

We here focus on bilateral adaptation aid, and specifically the question of distribution. Parties to the climate change negotiations agree in principle that the countries that are 'particularly' vulnerable to the adverse effect of climate change should be prioritized (e.g. UNFCCC 2009: paragraph 3; UNFCCC 2015: paragraph 9). But how does this commitment to prioritizing countries particularly vulnerable to climate change translate into actual adaptation aid allocation? To what extent do vulnerable countries receive more adaptation aid?

The adaptation finance architecture is fragmented, with many different sources and different channels, both multilateral and bilateral, though bilateral adaptation aid predominates: most adaptation finance comes as ODA (Barrett 2014: 131; Khan and Roberts 2013: 183). The fragmented adaptation finance architecture with its multiplicity of providers risks adverse effects. Khan and Roberts (2013: 180) lament in this context 'a serious lack of coordination in adaptation finance', and remark that the 'distribution of adaptation finance to highly vulnerable countries and to the most vulnerable people within recipient countries remains uneven, and uncertain'.

[1] All monetary values are in current US dollars unless otherwise specified.

We here empirically examine how donors allocate their bilateral aid for adaptation, and specifically examine the role of vulnerability in allocation decisions. Our starting point is that we have institutional fragmentation (see introduction to the special issue), but that this does not necessarily imply norm fragmentation. We specifically test the extent to which fragmented bilateral adaptation aid aligns with the collective UNFCCC goal of prioritising highly vulnerable countries. We address this question using data from the Organisation for Economic Cooperation and Development (OECD) from 2011 to 2014. Our analysis indicates that bilateral aid indeed aligns with the UNFCCC priority to vulnerable countries. Countries classified as vulnerable by different vulnerability indicators tend to receive relatively more adaptation aid. Donors also provide relatively more aid to middle-income countries, to democracies, and to countries with small populations (at least in absolute terms). Importantly, our findings also point to the inherent difficulties of measuring vulnerability. Identifying countries that are (particularly) vulnerable to climate change requires fundamentally political and normative decisions that are hard to capture with quantitative indicators (e.g. Klein 2009). The analysis here thus primarily serves as a starting point for more detailed analyses of decision-making processes around adaptation aid.

The remainder of this paper is structured as follows: The next section discusses the literature on aid allocation and specifically on the allocation of adaptation aid, and derives hypotheses regarding adaptation aid. Section 3 discusses the methods and data used in the paper, and section 4 presents the empirical results of our models. The last section concludes.

2. The Political Economy of (Adaptation) Aid

A growing body of literature focuses on adaptation and on adaptation aid, including on its allocation. Several authors provide normative arguments for how adaptation aid *should* be allocated, with most emphasizing the need for prioritizing vulnerable countries: adaptation aid should first and foremost support the vulnerable, and specifically those 'particularly vulnerable' to climate change (e.g. Barr et al. 2010; Ciplet et al. 2013; Duus-Otterstrom 2015; Grasso 2010a;b).

The few empirical studies on actual allocation of adaptation aid, however, find limited evidence for vulnerable countries being given priority. Several studies examine funding decisions of the multilateral Adaptation Fund; they conclude that the Adaptation Fund does *not* accord priority to vulnerable countries (Persson and Remling 2014; Remling and Persson 2015; Stadelmann et al. 2014). Robertsen et al. (2015) focus on bilateral aid from seven donors to sub-Saharan Africa. Their results similarly suggest that donors do not take into account vulnerability in their allocation decisions: neither poorer nor more exposed countries receive more adaptation aid. Barrett (2014) analyses the allocation of adaptation aid at the subnational level in Malawi. His analysis indicates that districts with high physical vulnerability receive more adaptation finance, but not those with high socio-economic vulnerability. Betzold (2015) investigates Germany's adaptation aid, and finds that political and economic interests matter more than vulnerability. Thus, so far there is little evidence that vulnerability matters for adaptation aid allocation.

Nevertheless, developed countries have agreed, in principle, to allocate their adaptation aid according to the aforementioned justice or equity perspective. As early as 1992, the UNFCCC stipulated that developed countries 'assist the developing country Parties that are particularly vulnerable to the adverse effects of climate change' (UNFCCC 1992: paragraph 4(4)), with later agreements confirming the focus on 'particularly vulnerable' countries, without, however, necessarily identifying who these are (e.g. UNFCCC 2009: paragraph 3; UNFCCC 2010: paragraph 11; UNFCCC 2015: paragraph 9).

In other words, adaptation aid should be disbursed on the basis of need: the more assistance a country needs to adapt to climate change, the more assistance it should get. Need, for development aid in general, has been mainly understood as poverty, measured by per capita income; accordingly, the poorer a country, the more development aid it should receive (e.g. Berthélemy 2006; Clist 2011). In an adaptation context, need translates as vulnerability to climate change impacts: the more vulnerable a country, the higher its need for support with adaptation, and therefore the more adaptation aid it should receive.

Vulnerability to climate change is an inherently complex concept with no single definition. Nonetheless, 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). In line with these two dimensions of vulnerability, we expect a positive relationship between adaptation aid and exposure, and a negative relationship between adaptation aid and adaptive capacity:

> **H1a:** The more exposed a recipient country to the adverse effects of climate change, the more adaptation aid it will receive.
>
> **H1b:** The lower the adaptive capacity of a recipient country, the more adaptation aid it will receive.

We know from the literature on adaptation aid, as well as from the wider literature on aid allocation, that other factors beyond recipient need play a role in allocation decisions. Donors also use their aid to reward recipient merits, as well as to promote their own political, economic and security interests (e.g. Alesina and Dollar 2000; Berthélemy 2006; Clist 2011; Hicks et al. 2008; Hoeffler and Outram 2011). However, here we are mainly interested in the role of recipient need, that is, vulnerability to climate change, and its influence on allocation patterns at the aggregate level across all donors..

3. Data and Method

We test for the role of vulnerability empirically with a newly compiled dataset that covers 144 developing countries for the period 2011 to 2014. The following sections explain the individual variables in our dataset as well as our statistical models.

3.1. Dependent Variable: Adaptation Aid

Our dependent variable is the level of adaptation aid flowing to developing countries. We rely on data from the Organisation for Economic Co-operation and Development (OECD) Creditor Reporting System (CRS), and hence on donors' self-reported adaptation aid. This is problematic, as donors tend to over-report (Junghans and Harmeling 2012; Michaelowa and Michaelowa 2011), but we need comparable data across all donors. The OECD provides a common reporting frame and has more coverage than for instance the UNFCCC's biennial reports. The latter reports have no agreed definition of climate finance, which makes "it difficult to compare the official climate finance statistics across Biennial Reports" (Francke et al. 2015: 36).

In contrast, the OECD introduced a marker for adaptation in 2010. Accordingly, 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).[2] We use adaptation aid as dependent variable both on a per capita basis and as a percentage of the total adaptation aid flows to developing countries in a given

[2] The OECD CRS distinguishes between aid projects with adaptation as their principal objects and aid projects with adaptation as a significant objective. The former projects would not have taken place if it was not for adaptation, while the latter would have taken place even without adaptation, but are still important for adaptation (OECD 2011: 5).

year. Both dependent variables represent aggregate aid flows, i.e. all flows from donor countries to a specific recipient country in a year are combined. For the per capita variable, all adaptation aid flows per capita to the country in a given year were summed up, i.e., we examine how much bilateral adaptation aid a country receives from all donors combined. For the percentage of total aid variable, we added all adaptation aid flows to a country in a given year together, and calculated the fraction this sum represented compared to all adaptation aid flows to all countries in the same year. This second dependent variable also helps to counter the problem of over-reporting. We expect all donors to over-report. By studying the distribution of the total amount of adaptation aid in percent, we obtain a good picture of allocation regardless of the actual amount of adaptation aid. By construction, we have repeated observations for the same recipient countries, and thus a nested data structure. We therefore use multilevel models to take this data structure into account.[3]

In 2010, the first year the OECD CRS uses the adaptation marker, considerably less funds were allocated to (or registered as) adaptation aid, possibly because not all project that benefitted adaptation efforts were marked as such. For this reason we consider this first year to be a learning period, for which a different allocation logic (and thus a different data generating process) could apply. Accordingly, we start our analysis in 2011. For the OECD CRS data both commitments of adaptation by donors and actuals disbursements of funds to recipients are available. We use commitments rather than disbursements because they reflect, as Berthélemy (2006: 80) argues, 'much better than the latter the decisions made by the donors: disbursements are influenced by the capacity of the recipients to meet the donors' conditionalities'.

3.2. Recipient Need

Our main explanatory variable is vulnerability to climate change. There is little agreement on how to measure vulnerability. Brooks et al. (2005) for instance provide a long list of potential proxies to measure vulnerability to climate change at the national level, which includes data on economic performance, governance, education, as well as geography and ecology (Brooks et al. 2005: 155; see also e.g. Barnett et al. 2008). This list is almost too long to be useful, and includes variables that could also be used to measure recipient merit or donor interests. For our first hypothesis, we focus on the

[3] Since we use aggregate data to capture recipient focused explanations of adaptation aid we only have 15 observations with entries of zero. For this reason we do not use a Tobit model, as is often used in the literature. Further, because the data reported do not allow us to differentiate between entries that are zero and those that are missing, all empty cells have been coded to represent zero. We believe that in such cases no adaptation aid has been reported to the OECD, and that this procedure is justified. We therefore do not apply Heckman selection models either.

geophysical dimension of vulnerability, and use several measures to capture the different impacts of climate change.

A first proxy is the percentage of the population living below an elevation of five meters – an indication of exposure to sea-level rise, which is certainly a central climate change impact that is also very present in political and public debate. Data comes from the Center for International Earth Science Information Network (CIESIN). Since the last comprehensive data available is for the year 2000, we use that for all years (CIESIN 2012).

Another key climate change impact is the increased frequency and intensity of extreme weather events. To capture this impact, we use the Global Climate Risk Index (CRI). The index is based on losses – human and economic – from climate-related weather extremes such as droughts, floods and storms, and has been computed by the organisation Germanwatch since 2006.[4] The CRI scores of the countries in the dataset range from 2.5 for Thailand in 2012 (highest vulnerability) to 126.2 for various countries in the same year (lowest vulnerability). In order to facilitate the interpretation of the regression coefficients below, we reversed the variable such that the lowest vulnerability is at 1, with higher values indicating higher levels of vulnerability. A positive regression coefficient therefore indicates that more vulnerable countries obtain more adaptation aid.

The Secretariat of the Pacific Community's Applied Geoscience and Technology Division (SOPAC) provides a more general Environmental Vulnerability Index (EVI). The EVI is based on 50 indicators 'for estimating the vulnerability of the environment of a country to future shocks' (SOPAC 2004). The 50 indicators fall under several issue areas or sub-indices.[5] We only use the EVI's Climate Change Subindex as a third proxy for vulnerability. The Climate Change Subindex covers 13 of the 50 indicators and is time-invariant. It ranges from 1 to 7, with higher scores indicating higher vulnerability (for a detailed description, see Kaly et al. 2004). Since the EVI predicts long-term vulnerability, there are no annual data and we use the same value for each country-year.

Vulnerability depends also, and crucially, on adaptive capacity, as our second hypothesis reflects. Adaptive capacity depends on many factors, including information, awareness, social cohesion, technology, and resources (see e.g. Barnett 2008). As a somewhat rough proxy, we include financial

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[4] See the reports on www.germanwatch.org/en/cri.

[5] These sub-indices are climate change; biodiversity; water; agriculture and fisheries; human health aspects; desertification; and exposure to natural disasters. See Kaly et al. (2004).

resources to capture adaptive capacity, measured by gross domestic product (GDP) per capita, in constant 2005$.[6] While poorer countries, less able to respond to the challenges of climate change by themselves, should receive more aid, research on development aid has found a non-linear effect of income: poorer countries receive more aid, but very poor countries receive in fact less aid than their income level would predict (cf. Neumayer 2003b). To capture possible non-linear effects, per capita income is entered into the regressions in linear as well as quadratic form (Alesina and Dollar 2000; Neumayer 2003a). The data is taken from the World Bank (World Bank 2014).[7]

Policy documents from the climate change negotiations specifically recognize least developed countries (LDCs), small island developing states (SIDS), and African countries as particularly vulnerable to climate change (e.g. UNFCCC 2009). Many of these countries are exposed, but importantly, they also have low adaptive capacity. As a final proxy for vulnerability, we here use a dummy variable for belonging to one (or more) of these groups of countries. Since the three groups partly overlap, we use only one dummy to avoid correlation problems.

3.3. Control Variables

Beyond vulnerability, we expect that recipient merit as well as donor interests play a role, which is why we introduce several control variables in our model.

To capture recipient merit, we focus on two measures. First, we use the level of democracy, as democracies tend to receive higher levels of aid, and possibly also higher levels of adaptation aid. Unfortunately, many measures of democracy such as the Polity IV index do not include small states like the SIDS, yet we need data on the level of democracies for as many countries and years in our dataset as possible. Therefore, we opt for data from Freedom House, which has the widest coverage, both temporally and spatially. Following Neumayer (2003a) and others (e.g. Clist 2011), we use the Freedom index, the sum of Freedom House's measures of political rights and civil liberties. The index is recoded, such that higher values indicate higher levels of freedom, and data is from Teorell et al. (2015).

[6] We use constant dollars because there are slightly more observations compared to purchasing power parity, and to ensure that the entries are on the same scale across the years. In any case, the two GDP measures are highly correlated (correlation coefficient of over 0.9)

[7] There exist two additional indices trying to capture vulnerability to climate change impacts: The ND-GAIN index and the DARA index. Both indices combine variables capturing the geophysical and the socio-economic dimension of climate change, which is, in our view, not ideal for the purpose of this paper. In addition, the DARA index only divides countries into five categories of vulnerability. For these reasons we do not use these two indices in this paper.

As a second measure capturing recipient merit, we include the 'Control of Corruption' variable from the Worldwide Governance Indicators (Kaufmann et al. 2011; 2014). This variable is also available for all countries in our dataset, and lower levels of corruption are a good indicator for the capacity of countries to make good use of the funds provided by donors. The variable is by design standardized, i.e. it has a mean of zero and a standard deviation of 1. However, since donor countries, which on average exhibit lower levels of corruption, are not part of our recipient-focused dataset, the mean in our data is -0.47 and the standard deviation is 0.66.

Furthermore, we control for two additional variables. First, the level of total development aid a country receives might be a good predictor of how adaptation aid is disbursed, if donor countries follow similar distribution logics. These aid data are taken from the World Bank (2014). Second, we control for a country's population. The literature on aid allocation has found a 'small country bias': while unclear why, studies find that countries with small populations receive relatively more aid on a per capita level (e.g. Alesina and Dollar 2000; Neumayer 2003a). Population data is taken from the United Nations (United Nations Statistics Division 2014).[8]

We also would like to control for donor interests in the models. However, a robust analysis for donor interests requires a dyadic dataset. We do not develop a dyadic dataset for three reasons. First, the main variables in the study (total donations received by a country, vulnerability to climate change impacts) are not in dyadic form. In addition, our research question does not ask whether different donors consider vulnerability differently when distributing money, but how, on aggregate, vulnerability affects how much money developing countries receive. From the perspective of the research design, using aggregate data is appropriate for this study. Second, control variables are included to avoid omitted variable bias. Omitted variable bias arises when the variable that is not included both influences the dependent variable and is correlated with the independent variable in question. A country's vulnerability to climate change is unlikely to be correlated with trade data or other measures of donors' economic and political interests, such that the danger of omitted variable bias caused by not including such dyadic variables is, in our opinion, relatively small. Finally, there are serious data availability and reliability problems with many dyadic donor interest variables such as bilateral trade. We would not only risk losing many of the small island developing states, for which data generally is rare, but which we consider important to answer our research question. Also, trade

[8] Note that the population for Niue is from the Secretariat of the Pacific Community. For a full list of variables, descriptive statistics and data sources, and a correlation table, see Tables 4, 5, and 6 in the appendix.

and similar data tend to be inconsistent and suffer from measurement error. For all these reasons, the costs of including this variable into the model outweigh, in our opinion, the benefits of developing a dyadic dataset. We therefore rely on aggregate data in the models below to assess our hypotheses.

The econometrics of aid allocation is technically debated, notably because dyadic dataset contain a large number of zeroes, as not all donors provide aid to all developing countries. A general response to this problem is to distinguish between a selection stage and an allocation stage (e.g. Berthélemy 2006; Clist 2011). Here, however, we only look at aggregate aid flows, such that almost all countries receive at least some adaptation aid. Accordingly, we exclude the selection stage and only look at the allocation stage. Since the observations are nested within countries we use hierarchical models with country random effects and robust standard errors. With only a few observations per country, random effects are more stable than fixed effects, since the shrinkage back to the mean stabilizes them and makes them less susceptible to the influence of outliers (Clark and Linzer, 2014).

Given the high variance and skewed distribution of adaptation aid, income, and population, these variables enter the regressions as their natural logarithm. To avoid potential reverse causalities, the variables for income, democracy, control of corruption, foreign direct investment, and deaths and losses from extreme weather events are lagged by one year. Additionally, to account for time effects, year-fixed-effects are included as additional predictors (but not reported).

4. Results

Although (bilateral) adaptation aid is still just a very small proportion of overall development aid (see Figure 1a), it has increased since the Rio Marker for adaptation was introduced in 2010 (see Figure 1b). In 2010, OECD bilateral aid to individual developing countries that targeted adaptation totalled \$5.3 billion. For projects worth \$3.3 billion (62%), adaptation was a significant objective, for projects worth \$2 billion (38%), it was the principal objective.[9] In 2014, the year with the highest aid flows on record so far, total adaptation aid had increased to over \$9.3 billion, of which almost \$5.8 billion (62%) had adaptation as significant, and \$3.5 billion (38%) as principal objective. Translated to per capita aid, this means that on average, each individual in the developing world obtained about \$1.57 in 2014 for adaptation measures, up from just below \$1 in 2010.

[9] Note that these figures differ from official OECD statistics (e.g. OECD 2014) because they exclude aid going to regional or unspecified recipients.

*** Figure 1 about here ***

When we look at which countries received most adaptation aid over the entire period of analysis, per capita as well as in percent of all adaptation aid (Tables 1a and 1b, respectively), the results seem to confirm that donors privilege vulnerable countries, such as SIDS. The top ten per capita adaptation aid recipients are all SIDS. The recipient with most per capita aid, Niue, is freely associated with New Zealand, as is the Cook Islands; both traditionally receive very high levels of support from New Zealand. Given the very small population of Niue, which has just about 1,500 inhabitants, the extremely high level of adaptation aid of just under $13,000 per capita from 2010 to 2014 is less surprising. The picture is different if we look at how much single countries obtained of the so far disbursed adaptation aid (in percent). Unsurprisingly, larger countries receive more aid in total then smaller ones. Vietnam, having received 7.52% of all adaptation aid so far committed, ranks first, followed by India (7.20%) and the Philippines (4.22%). Other large recipients include Bangladesh (3.58%), China (3.02%), Kenya (2.90%), Indonesia (2.78%), and Ethiopia (2.73%).

*** Table 1 about here ***

Let us turn to a more rigorous test of who receives adaptation aid. Table 2 reports the results from the hierarchical regression models for per capita adaptation aid; Table 3 for adaptation aid in percent of all adaptation aid committed that year. The models use the various indicators for vulnerability introduced earlier: Model 1 measures vulnerability using the CRI and the EVI climate sub-index. The former indicator looks back at a given year, and judges how strongly affected countries had been by weather related events. In contrast, the EVI index assesses how vulnerable countries are to potential future changes in weather, floods, etc. In other words, the first index captures highly visible phenomena that influence donors at the time when they decide how to allocate funds, while the second index operationalizes vulnerability as a long-term concept. Thus, these two indices are highly complementary, and we combine them in the first model. Model 2 combines the percent of population living below an elevation of five meters with the vulnerability dummy combining African countries, SIDS and LDCs. We put these variables into the same model because they are not composite indices as the EVI and the CRI, and are therefore easier to understand for policy-makers as indicators of vulnerability. Model 3 is a full model including all variables of the previous two models. All three models include GDP per capita and GDP per capita squared to also capture the socio-economic capability of countries to deal with climate change impacts, and the control variables control of corruption (WGI), the Freedom index, total population, and total development aid. Figures 2 and 3 graphically depict the effects of the statistically significant variables related to recipient need.

*** Table 2 about here ***

*** Table 3 about here ***

First, let us answer the question whether countries more exposed to climate change impacts actually receive more adaptation aid, as proposed by H1a. The results indicate that donors indeed take into account physical vulnerability when allocating adaptation aid. Overall, the regression models suggest that countries vulnerable to extreme weather events, as measured by the CRI, do receive significantly more adaptation aid, both per capita and in percent of all adaptation aid. The CRI is highly significant in all models for both dependent variables. The panels (a) of Figures 2 and 3 depict the effect of the CRI graphically for the two full models. As can be seen in Figure 2, from the lowest to the highest levels of vulnerability the predicted adaptation aid per capita increases, all else being equal, by almost \$3. In terms of percentages, the most vulnerable countries can expect about 0.3% more of the totally committed adaptation aid each year than the least vulnerable countries.

The EVI climate sub-index is significant in most models, although in the per capita models the coefficients are only significant at the 10% level (the partial Model 1 of Table 2) or insignificant (the full Model 3). Still, donors also seem to consider the long-term consequences of climate change when deciding how to allocate adaptation funds. Panel (b) of Figure 3 shows the EVI effect for the percentage model. As can be seen, the most vulnerable countries can expect about 0.5% more adaptation aid than the least vulnerable countries. In the per capita model (not graphically illustrated as the significance level is too low) this would translate into an increase of over \$3 per capita for particularly vulnerable countries. Thus, our models predict that countries exhibiting both short-term (CRI) and long-term (EVI) vulnerability will obtain substantially more adaptation funds than their less vulnerable peers.

*** Figure 2 about here ***

*** Figure 3 about here ***

Adaptation aid is also strongly related to the percentage of the population living in low-lying areas (the coefficient is highly significant across all models). In contrast, African countries, SIDS, and LDCs (the vulnerability dummy) do *not* receive more adaptation aid on a per capita basis, despite being singled out as particularly vulnerable in the climate change negotiations. On a percentage of total adaptation aid basis, the effect is significant in both models, yet only at the 10% level for the full model. One should, however, not rush to the conclusion that these highly vulnerably countries, particularly SIDS, do not receive more funds than other countries because the regression coefficient is insignificant. As we saw in Table 1, SIDS are among the countries receiving most adaptation aid on a per capita basis (over the entire five-year period). And only when we enter the vulnerable dummy into the regression are they predicted to receive about $2 more per capita each year than other countries. However, when we control for their (often small) population size and their high vulnerability levels, the significance of this effect disappears. These countries still obtain more funds, but the extra aid is explained by the covariates, and being an African country, a LDC, or a SIDS does not contribute to receiving aid in addition to the already high sums that smaller and more vulnerable countries obtain.

The effects of the percentage of the population living below five meters altitude is depicted in panel (b) of Figure 2 for per capita adaptation aid, in in panel (c) of Figure 3 for the percentage of total adaptation aid. The figures were clipped for values larger than 40%, because only very few countries have such vast numbers of people living at sea level, and as a consequence the confidence intervals become very wide and are not very meaningful. Yet, the figures show that countries with around 40% of the population living in very low lying areas are predicted to receive about $2 more per capita than countries where only very few people live in such areas, and about 0.25% more of the annually disbursed adaptation funds. This, again, may become a substantial difference in the future when adaptation funding increases.

Regarding the socio-economic capability of countries (H1b), the poorest countries do not appear to receive more adaptation aid. Instead, the analysis confirms a bias toward middle-income countries.

Rather than giving more aid to the poorest countries, donors prefer to allocate funds to middle-income countries. More per capita income is associated with more adaptation aid, both in per capita terms and as a percentage of the annually committed funds. Yet, the bias is reversed at some point, as the negative and very significant relationship between the quadratic term and adaptation aid suggests. Thus, middle-income countries benefit most from adaptation aid, possibly because these countries are (perceived to be) better able to absorb incoming aid flows. This relationship is graphically depicted in panel (c) of Figure 2 for per capita adaptation aid, and in panel (d) of Figure 3 for the percentage of total annual funds. Both figures show that the lowest income countries receive relatively little adaptation aid, yet this changes quickly as GDP increases. For per capita aid, the maximum is reached at a per capita GDP of almost exactly $1,000, at which point countries are expected to receive slightly over $6.5 per capita, about $4.5 more than the poorest countries. Thereafter, aid per capita drops again (yet more slowly than it rises at the beginning), and the richest countries in the dataset are predicted to receive less than $1 per capita in adaptation aid. The situation is similar when we consider the percentage of annual adaptation aid countries obtain (panel (d) of Figure 3). Yet this second model predicts the maximum aid countries receive to be earlier at a per capita GDP of around $890. At this level, countries are predicted, all else equal, to receive about 1.7% of the annually disbursed adaptation funds, while the poorest countries receive around 1.4%, and the richest around 1.1%.

Overall, then, our evidence indicates that vulnerability matters for the allocation of adaptation aid, both in terms of exposure to climate change impacts, but also in terms of adaptive capacities. Thus, we consider H1a and, to a lesser extent, H1b to be substantiated.

Let us now turn briefly to some of the control variables in the model. First, countries with less corruption receive significantly more funds. Such countries are not only (seen as) better able to absorb funds, as middle-income countries are compared to the poorest countries, but also more likely to utilize funds as intended, rather than divert them for private gains. The effect of corruption control is significant across all models for both dependent variables. According to the models, the least corrupt countries are expected to receive almost 0.65% more of the annually committed adaptation aid than the most corrupt states. In dollar terms, this means they receive about $4.5 extra for each citizen each year. This is an indication that donors also consider recipient merits when they allocate adaptation funds.

The effect of the Freedom index, on the other hand, is not significant in the models. However, this is likely a result of the high correlation between the Freedom index and the WGI control of corruption variable. When the latter is removed, the Freedom index becomes highly significant and has the expected sign. In other words, it then explains the variance previously taken up by the corruption control variable. In effect, one single quantity capturing recipient merits is enough in the models, since all these variables are highly correlated with each other.[10]

The analysis also finds that donors take into account population size: as with general development aid, small countries receive relatively more adaptation aid per capita, while large countries (unsurprisingly) receive a higher share of the total adaptation aid committed. The relationship is significant in all models. The other variables in the models are either insignificant, or show only low levels of significance, and are therefore not further discussed here.

5. Conclusion

Adaptation, along with adaptation aid, has gained increasing prominence on the international climate change agenda. Despite this growing attention, adaptation aid allocation across developing countries has not been studied so far. The present article is a first step towards filling this research gap. We started to explore the question of how donors allocate their bilateral adaptation aid to developing countries. We particularly focused on the question whether particularly vulnerable countries – measured both as sensitivity to climate change impacts and as adaptive capacity – receive more adaptation aid, as promised repeatedly by donor countries during international negotiations, and as we would expect from a justice or equity perspective.

In contrast to several other studies that examine the allocation of adaptation aid (e.g. Persson and Remling 2014; Remling and Persson 2015; Stadelmann et al. 2014; Betzold 2015), we find that vulnerability is an important predictor for the allocation of adaptation aid. Countries that are more vulnerable to climate change – as measured by different vulnerability indicators – receive more adaptation aid. In particular exposure to extreme weather events, as measured by the Global Climate Risk Index, is a good predictor for how much aid developing countries receive each year. We were able to demonstrate that the most vulnerable countries receive about $3 per year for each citizen more than the least vulnerable countries, or about 0.3% more of annually committed adaptation funds. Similarly, longer-term assessments of vulnerability to climate change impacts, as the Environmental

[10] When using another WGI variable such as government effectiveness, or another measure for democratic quality, e.g. the Polity IV scores, we always obtain very similar results, i.e. the coefficients are significant and have the expected sign. The other variables in the models are not greatly affected when the variable capturing recipient merit is changed.

Vulnerability Climate Change Sub-Index (Kaly et al. 2004), which captures how strongly climate change will be felt in a given country in the future, seem to influence how policy-makers distribute funds earmarked as adaptation aid. For this indicator, our models predict that the most vulnerable countries obtain, all else equal, about 0.5% more of the annually distributed aid than the least vulnerable countries. Furthermore, our models predict that states where many citizens live in high risk, low lying areas receive at least $2 more than high-lying countries.

In addition to exposure to climate change impacts, we also tested whether adaptive capacity, measured by a country's GDP per capita, plays a role for donors' disbursement decisions. We find that very poor countries receive relatively little aid, but also that aid flows increase relatively quickly as income increases, presumably because these countries are more capable of absorbing funds and to use them as intended. Lower middle-income countries obtain over $4 more than the poorest states; then the level of adaptation aid starts declining again, and the richest countries in our dataset are also those receiving least. All these results are in line with our expectations.

That donors do consider the vulnerability of countries when they earmark funds for adaptation aid projects is good news for recipient countries, but also for the fragmentation of the overall climate finance system. We find no evidence for norm fragmentation despite considerable institutional fragmentation. On the other hand, if vulnerable countries get significantly more adaptation aid, the difference is small in absolute terms, at about $3 or 0.3%. Whether this is fair or enough is questionable. Further, our analysis is only a first step, and has several limitations: we use aggregate data, consider only the period 2011 through 2014 and rely on donors' own classification of adaptation aid. Additionally, we only consider allocation among different developing countries, but not distribution within recipient countries; we therefore cannot be sure that adaptation aid reaches those most vulnerable communities and individuals *within* a country (cf. Barrett 2014; Duus-Otterström 2015). Finally, vulnerability is *per se* a contested concept that is difficult to measure at the national as well as at the sub-national level. Vulnerability is about the potential for loss, and hence about values: it is about identifying what is at risk of loss and whether that would be an acceptable or unacceptable loss – an inherently subjective process (Barnett et al. 2008). Identifying who is vulnerable and who should receive adaptation aid is therefore fundamentally a political decision (see Klein 2009).

Analyses that seek to relate adaptation aid to vulnerability are clearly fraught with ambiguity. Nonetheless, research as well as policy should seek to track as well as evaluate climate finance flows, including for adaptation, and this at the international, national but also sub-national levels. There is a need to understand better where adaptation aid is flowing to, and – equally if not more important – when and how this aid effectively supports adaptation and reduces vulnerability for the recipients. Developed countries have an obligation to assist developing countries in their efforts to respond to climate change, not only out of justice considerations but also according to the UNFCCC and later agreements. That this assistance reaches the vulnerable, and really helps and reduces vulnerability to climate change impacts should be a prime concern for donors and recipients alike.

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Table 1: Top recipients of adaptation aid (a) per capita, and (b) in percent of all adaptation aid

(a)

	country	adaptation aid (per capita)
1	Niue	12998
2	Tuvalu	3018
3	Cook Islands	1480
4	Nauru	740
5	Vanuatu	724
6	Kiribati	635
7	Dominica	576
8	Cape Verde	459
9	Samoa	419
10	Palau	397
	average*	183

(b)

	country	adaptation aid (percent of total of global aid)
1	Vietnam	7.52
2	India	7.20
3	Philippines	4.22
4	Bangladesh	3.58
5	China	3.02
6	Kenya	2.90
7	Indonesia	2.78
8	Ethiopia	2.73
9	Peru	2.24
10	Tanzania	2.02
		of total of $37.9 bn

* average without Niue: $94. Numbers are aggregates over the period 2010-2014

Table 2: Allocation of per capita adaptation aid

	Dependent variable:		
	Adaptation Aid per Capita (logged)		
	(1)	(2)	(3)
Climate Risk Index +	0.004***		0.005***
	(0.002)		(0.002)
Climate Sub-Index	0.145*		0.085
	(0.088)		(0.092)
Population below 5m		0.012**	0.010**
		(0.005)	(0.005)
Vulnerable country (dummy)		-0.014	0.048
		(0.139)	(0.135)
GDP/capita (logged) +	3.754***	3.422***	3.602***
	(0.737)	(0.768)	(0.747)
GDP/capita, squared +	-0.274***	-0.250***	-0.262***
	(0.050)	(0.052)	(0.050)
WGI: Corruption +	0.280**	0.228*	0.305**
	(0.135)	(0.134)	(0.134)
Freedom Index +	0.011	0.032	0.011
	(0.024)	(0.024)	(0.023)
Population (logged) +	-0.352***	-0.324***	-0.328***
	(0.036)	(0.037)	(0.038)
Total dev. aid (logged) +	0.025*	0.025*	0.029**
	(0.015)	(0.015)	(0.015)
Constant	-6.691**	-5.587**	-6.573**
	(2.663)	(2.845)	(2.774)
Observations	462	478	462
Log Likelihood	-614.296	-651.933	-612.204
Akaike Inf. Crit.	1,256.592	1,331.866	1,256.408
Bayesian Inf. Crit.	1,314.490	1,390.241	1,322.577

Note: The models are hierarchical models with country random effects and robust standard errors in parentheses. Yearly data lagged (marked +) by one year; year dummies included (not shown). * p<0.1; ** p<0.05; *** p<0.01

Table 3: Allocation of adaptation aid, percent of yearly total

	Dependent variable:		
	Adaptation Aid (Percent of Total, logged)		
	(1)	(2)	(3)
Climate Risk Index +	0.002**		0.002**
	(0.001)		(0.001)
Climate Sub-Index	0.108***		0.085**
	(0.039)		(0.041)
Population below 5m		0.006***	0.004**
		(0.002)	(0.002)
Vulnerable country (dummy)		0.078	0.094*
		(0.051)	(0.051)
GDP/capita (logged) +	0.627*	0.590*	0.651**
	(0.321)	(0.327)	(0.321)
GDP/capita, squared +	-0.049**	-0.044**	-0.049**
	(0.022)	(0.022)	(0.022)
WGI: Corruption +	0.128**	0.116**	0.132**
	(0.058)	(0.056)	(0.057)
Freedom Index +	-0.0001	0.006	0.004
	(0.010)	(0.010)	(0.010)
Population (logged) +	0.130***	0.146***	0.145***
	(0.016)	(0.016)	(0.016)
Total dev. aid (logged) +	0.004	0.005	0.006
	(0.006)	(0.006)	(0.006)
Constant	-3.942***	-3.919***	-4.399***
	(1.160)	(1.203)	(1.183)
Observations	462	478	462
Log Likelihood	-155.298	-156.665	-151.700
Akaike Inf. Crit.	338.595	341.329	335.399
Bayesian Inf. Crit.	396.493	399.704	401.568

Note: The models are hierarchical models with country random effects and robust standard errors in parentheses. Yearly data (marked +) lagged by one year; year dummies included (not shown). * p<0.1; ** p<0.05; *** p<0.01

Table 4: Data sources

Variable	Data source
Dependent Variable	
Adaptation aid, per capita *	OECD (2014)
Adaptation aid, percent of global total *	OECD (2014)
Recipient Needs	
Climate Risk Index +	Germanwatch
Climate Sub-Index (EVI)	Kaly et al. (2004)
Population below 5m	CIESIN (2012)
GDP per capita * +	World Bank (2014)
Vulnerable country group (dummy for country belonging to LDCs, SIDS or Africa)	UN-OHRLLS (2015a; b)
Control Variable	
Population * +	World Bank (2014)
Control of Corruption (WGI) +	Kaufmann et al. (2014)
Freedom Index (FH) +	Teorell et al. (2015)
Total development aid * +	World Bank (2014)

* natural logarithm used in regression analysis; + lagged variable used in regression analysis

Table 5: Summary statistics for all dependent and independent variables

	Min	Max	Median	Mean	Std. dev.	N
Adaptation aid per capita *	0	408.47	2.61	12.30	36.32	462
Adaptation aid (percent) *	0	16.47	0.27	0.81	1.47	462
Climate Risk Index +	2.17	126.20	78.85	72.85	32.30	462
Climate Sub-Index (EVI)	1.67	5.13	3.17	3.21	0.73	462
Population below 5m	0	100	2.86	7.38	13.63	462
Vulnerability dummy	0	1	0	0.44	0.49	462
GDP per capita * +	141	15450	1980	3037	3063	462
Control of Corruption (WGI) +	-1.62	1.56	-0.57	-0.47	0.66	462
Freedom Index (FH) +	2	14	9	8.31	3.35	462
Population (million) * +	0.053	1364.27	10.04	48.06	164.69	462
FDI in percent +	-1.08	66.01	3.58	5.46	7.74	462
Total trade (billion $) * +	0.15	4160	14.72	101.90	368.08	462
Total aid (million $) * +	0	6832	383.0	730.6	1023.19	462

* natural logarithm used in regression analysis; + lagged variable used in regression analysis

Table 6: Correlation Table

	Adapt. Aid (per capita)	Adapt. Aid (% of total)	Climate Risk Index	Climate Sub-Index	Popul. below 5m	Vulnerability dummy	GDP/capita	Population	WGI: Corruption	Freedom Index	Total development aid
Adaptation Aid (per capita)	1.00										
Adaptation Aid (% of total)	0.23	1.00									
Climate Risk Index	-0.07	0.36	1.00								
Climate Sub-Index	0.19	0.00	-0.08	1.00							
Popul. below 5m	0.29	-0.03	-0.14	0.37	1.00						
Vulnerbility dummy	0.14	-0.06	-0.15	-0.05	0.13	1.00					
GDP/capita	-0.02	-0.26	-0.11	0.29	0.10	-0.26	1.00				
Population	-0.50	0.54	0.40	-0.25	-0.32	-0.27	-0.29	1.00			
WGI: Corruption	0.25	-0.15	-0.10	0.26	0.07	0.04	0.51	-0.44	1.00		
Freedom Index	0.26	-0.08	0.04	0.23	0.10	-0.02	0.38	-0.34	0.66	1.00	
Total development aid	0.09	0.14	-0.04	-0.07	-0.15	0.13	-0.34	0.09	-0.21	-0.05	1.00

Figure captions

Fig. 1: Adaptation aid trends: (a) adaptation aid compared to overall (bilateral) development aid; (b) total (bilateral) adaptation aid.

Fig. 2: Substantiated effects ($p<0.05$) for per capita adaptation aid

Fig. 3: Substantiated effects ($p<0.05$) for adaptation aid as percentage of annual total