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Climate change adaptation finance: are the most vulnerable nations prioritised?

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Nicholas Saunders

Stockholm Environment Institute
Linnégatan 87D 115 23 Stockholm, Sweden
Tel: +46 8 30 80 44
www.sei.org

Author contact: Nicholas Saunders
nicholas.j.saunders@gmail.com
SEI contact: Adis Dzebo
adis.dzebo@sei.org
Editing: Emily Yehle
Layout: Richard Clay

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Abstract

In 2009, developed countries jointly agreed to raise US$100 billion per year in climate finance by 2020 (UNFCCC 2009). The total amount of adaptation finance has increased each year since then, but the extent to which allocations are in line with recipients' climate vulnerability is still debated in the literature.

This paper analyses the determinants of adaptation finance allocation using data sourced from the Organisation for Economic Co-operation and Development. All bilateral allocations reported between 2011 and 2015 and multilateral allocations reported between 2013 and 2015 are included in the analysis. A two-step hurdle model is used to explore both the intensive and extensive margin decisions of donors.

In contrast to previous research, the relationship between vulnerability to climate change and adaptation finance is found to be concave in both stages of the bilateral model. Diminishing and then negative returns to vulnerability are observed. On average, countries most vulnerable to climate change are found to receive smaller allocations of adaptation finance from bilateral donors than their less vulnerable counterparts.

While multilateral donors are found to allocate more adaptation finance to small island developing states, they are not observed to prioritise vulnerable nations in the selection stage. Overall, the allocation of adaptation finance is not found to be consistently aligned with the sentiment of the Paris Agreement, which stipulates that efforts should be made to provide financial resources to assist developing countries, with priority given to countries that are particularly vulnerable to the adverse effects of climate change.

Countries most vulnerable to climate change are found to receive smaller allocations of adaptation finance from bilateral donors than their less vulnerable counterparts.

1. Introduction

Climate change will impact the basic elements of life for people around the world, affecting health, food production and access to water (Stern 2007). Entire island nations are at risk of disappearing before the turn of the century (Locke 2009; Nurse et al. 2014).

Adaptation is thus key. In 2009, Parties to the United Nations Framework Convention on Climate Change (UNFCCC) recognized that the supply of international climate finance fell far short of the anticipated climate change mitigation and adaptation needs of developing countries. Developed countries thus committed to jointly raise US$100 billion a year in climate finance by 2020 at the 15th Conference of the Parties (COP15) (UNFCCC 2009). Post COP15, the amount of official development assistance (ODA) earmarked as climate finance increased rapidly. However, it is unclear if funding is indeed reaching the most vulnerable. The Paris Agreement stipulates that countries that are particularly vulnerable to climate change should be prioritised for funding and that donors should aim to achieve a balance between adaptation and mitigation (UNFCCC 2015). But most climate portfolios tend to preferentially target mitigation, despite a recognised need to increase adaptation finance (Buchner et al. 2014; Abadie et al. 2013).

In 2014 and 2015, an average of only 29% of bilateral ODA was specifically allocated to adaptation activities (OECD 2016). Recent studies suggest the annual cost of adaptation in developing countries could range from US$140 billion to US$300 billion by 2030, and from US$280 billion to US$500 billion by 2050 (UNEP 2016). In stark contrast to the level of need, only US$16 billion (2014 dollars) of adaptation finance was allocated to developing countries by bilateral and multilateral donors in 2015, according to data sourced from both the Organisation for Economic Co-operation and Development's (OECD) Creditor Rating System (CRS) and climate-related development finance at the activity level database. While the data shows a clear adaptation funding gap, the amount of adaptation finance allocated by donors annually has been increasing each year (OECD 2016; OECD 2019).

The extent to which a recipient nation's vulnerability to climate change drives donors' allocation decisions remains unclear in the literature. Two reports — the Development Initiatives' "Investments to End Poverty" report (2015) and OXFAM International's "Climate Finance Shadow Report" (2018) — found that the most vulnerable nations do not get the most adaptation finance, regardless of whether vulnerability is represented by the recipient's Least Developed Country (LDC) status, level of poverty, or vulnerability to climate change (Carty and le Compte 2018; Strawson et al. 2015). Conversely, more recent statistical analyses of donors' allocation patterns suggest that a recipient's physical vulnerability to climate change positively influences (albeit to varying degrees and levels of statistical significance) how much adaptation finance is allocated to it (Betzold and Weiler 2017; Robinson and Dornan 2017; Weiler et al. 2018; Bagchi et al. 2016).

Can these two presumably conflicting findings be reconciled? One explanation for the apparent disconnect is that one trend may be observed in the annual summary statistics, while another emerges once researchers consider additional explanatory variables and focus their analysis on the allocation patterns of individual donors (rather than considering pooled allocations). It is also feasible that a model that allows for the possibility of diminishing and then negative returns to vulnerability may better fit the data than one that assumes a linear relationship between vulnerability and allocation. There are, after all, a range of factors that disproportionately impede the ability of the most vulnerable states to access adaptation finance, such as the administrative burden associated with applying for funding and the dearth of bankable adaptation projects in vulnerable states (Leigland and Roberts 2007; Robinson and Dornan 2017).

In this working paper, I use a two-step (selection-allocation) hurdle model to explore the determinants of adaptation finance allocation, in order to test whether the most climate-vulnerable nations receive a smaller amount of adaptation finance on average than their less vulnerable counterparts, all else held constant. Both stages of the model include a squared vulnerability term to allow for the possibility of diminishing or negative returns to vulnerability. Data is organised in a year-donor-recipient panel triad to facilitate the analysis of finance allocations made by individual donors. Following the aid literature, indicators of recipient need, donor self-interest, and recipient merit are included in the analysis (Alesina and Dollar 2000; Berthélemy and Tichit 2004; Younas 2008).

This study makes a clear contribution to the literature by comparing bilateral and multilateral donors' allocation decisions. The bilateral dataset includes all allocations of adaptation finance reported to the OECD Development Assistance Committee (DAC) by nation states from 2011 to 2015; the multilateral analysis uses data from 2013 to 2015.[1] Considering bilateral and multilateral donors separately allows for an investigation into whether multilateral climate funds are more or less altruistic in their selection and allocation decisions than their bilateral counterparts.

I find strong support for a concave relationship between the vulnerability of a country to climate change and the probability that bilateral donors will select it as an adaptation finance recipient. In contrast, the results from the multilateral analysis indicate a negative relationship between the vulnerability of countries to climate change and their probability of selection. The most vulnerable nations are the least likely to be selected as finance recipients by both bilateral and multilateral donors. This finding contrasts previous studies by Betzold and Weiler (2016) and Weiler et al. (2018), which found a positive relationship between vulnerability and the probability of selection by bilateral donors. The concave relationship observed in the selection stage of the bilateral model is also present in the allocation stage. I find only limited support that multilateral donors prioritise the most vulnerable states in the allocation stage. On average, the results show that multilateral donors are less orientated toward recipient need than their bilateral counterparts.

The rest of this paper is structured as follows: Section 2 discusses the previous literature and gives context to the current study, Section 3 describes data and methods used to explore the research question, and Section 4 presents the findings. The discussion and conclusion follow in Sections 5 and 6, respectively.

1 Bilateral finance data from 2010 is not included in the analysis because submissions from several key donors were absent, suggesting they had not begun implementation of the adaptation marker. The same holds true for multilateral donors from 2010 to 2012. Multilateral development banks introduced their joint approach for measuring climate components in 2013 and started reporting to the DAC on 2013 flows (Inter-American Development Bank et al. 2018).

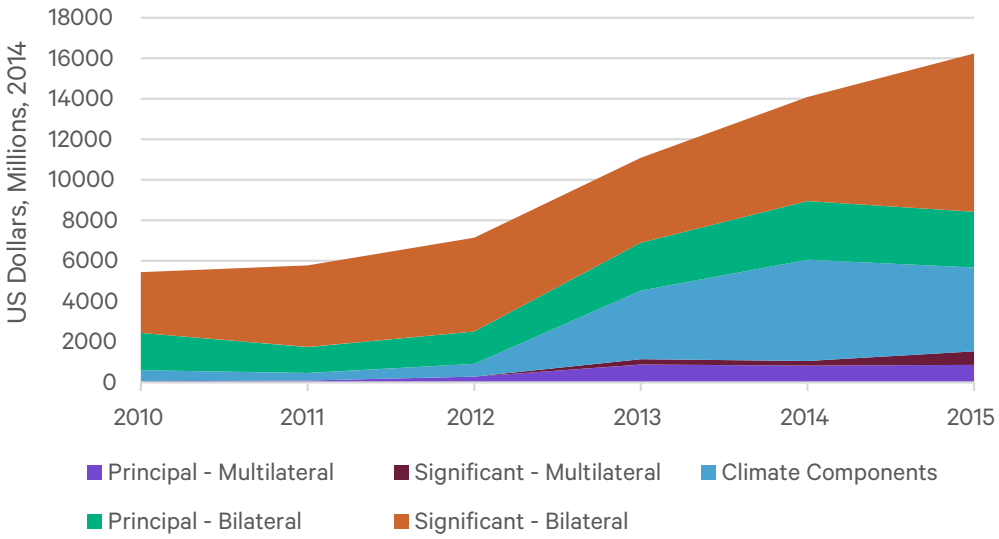
2. Context and previous research

2.1 Context

The climate finance landscape is complex; it includes public and private donors who allocate funds via a variety of financial mechanisms, including concessional and non-concessional loans, guarantees, equity, and grants. Allocations of adaptation finance by bilateral and multilateral donors are classified under two distinct frameworks: the OECD's Rio markers[2] and the Multilateral Development Banks' joint methodology for tracking climate adaptation finance. Under the Rio markers system, bilateral donors indicate finance is adaptation-related if it aims 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). Projects can either be marked as having a principal (primary) or significant (not primary) focus on adaptation. The Multilateral Development Banks (MDBs), on the other hand, report their adaptation-related development finance using the single-tiered "climate components/projects" marker (Inter-American Development Bank et al. 2018).[3]

The climate finance landscape is continually changing; in recent years, multilateral donors, both funds and banks, have significantly increased the amount of climate finance they provide. In 2017, MDBs provided USD$35.2 billion in climate finance, a 28% increase over the previous year (Inter-American Development Bank et al. 2018). As shown in Figure 1, the growth rate of different categorizations of climate finance is not consistent. If current trends continue, bilateral finance classified as significant and multilateral finance classified as "climate project/components" will ultimately far exceed other classifications of adaptation finance (Figure 1).

Figure 1. Adaptation Finance (OECD 2016 and OECD 2019)

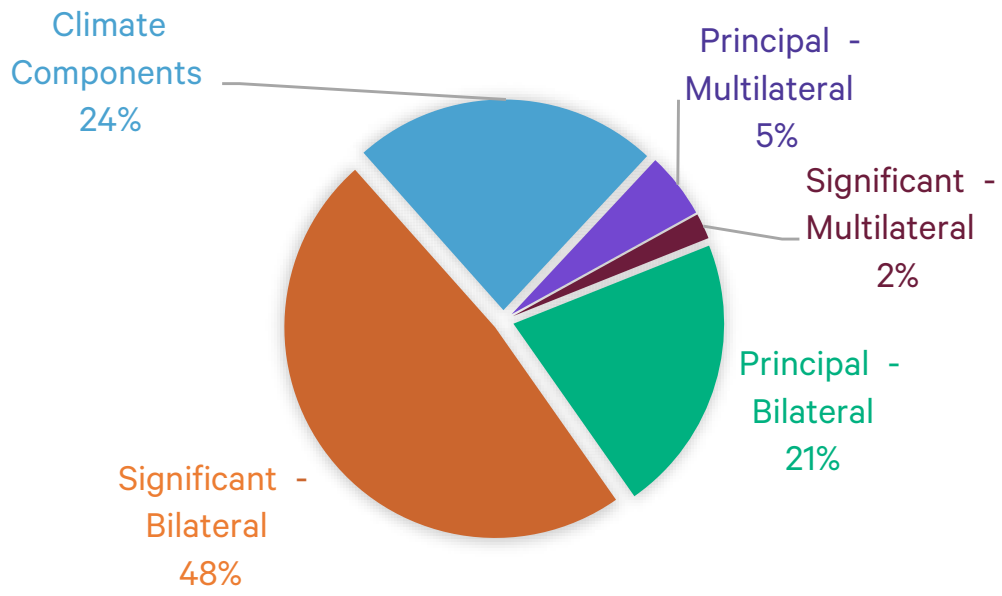


The breakdown of adaption allocated by category for both multilateral and bilateral donors between 2010 and 2015 is shown in Figure 2.

2 The scoring system for climate markers developed by the OECD consists of a three-tiered system wherein a funded activity qualifies as "principal" and receives a score of 2 points if there is a direct link between identified climate change vulnerabilities/ impacts and the project's activities (OECD 2011). If climate change adaptation forms part of the project, but is not the explicit focus, an activity can be classified as having a "significant" focus on climate change and be awarded 1 point. Projects with no focus on adaptation receive 0 points. See the Technical Appendix (Section 8.1) for a list of activities which qualify as "principal" under the OECD's climate change adaptation marker.

3 The MDBs that use the "climate projects/components" designation include the African Development Bank, the Asian Development Bank, the European Bank for Reconstruction and Development, the European Investment Bank, the Inter-American Development Bank, the International Finance Corporation, and the World Bank.

Figure 2. Percentage breakdown of the different classifications of adaptation finance allocated between 2010 and 2015 (OECD 2016; OECD 2019)



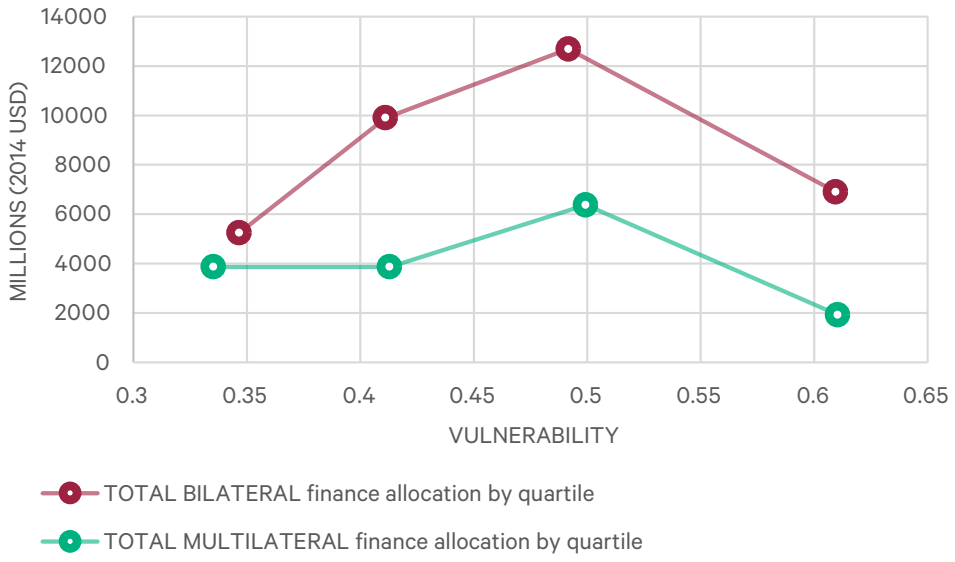
Even though the size of the pot is increasing, transaction costs for accessing resources are often high. Each donor often has its own individual requirements for eligibility, implementation, monitoring and reporting. This fragmentation places a considerable administrative burden on recipient countries — a burden that falls disproportionately on small and vulnerable states, which are less well equipped to meet the demands of individual donors (Robinson and Dornan 2017; Commonwealth Expert Group on Climate Finance 2013).

Given these difficulties, it is perhaps unsurprising that studies have shown that the aggregate allocation of adaptation finance does not appear to be in line with recipients' vulnerability to climate change (Strawson et al. 2015). Strawson et al. (2015) report that in 2013, only 9% of adaptation finance (in bilateral official development assistance) was allocated to countries with the highest level of vulnerability to climate change (the upper quartile of countries). When pooled, the data used in this study shows a similar trend; the total amount of finance allocated — from both bilateral and multilateral donors — increases in line with vulnerability up to a point, and then rapidly declines. This is evidence of a non-linear relationship between vulnerability and aggregate adaptation finance allocation (Figure 3).

Figure 3 suggests that bilateral donations are more responsive to recipient need. From quartile 1 (less vulnerable) to quartile 3 (more vulnerable), total bilateral finance allocated increases by approximately 100%, while multilateral finance increases by 50%. Furthermore, while both bilateral and multilateral allocations decrease between quartile 3 and quartile 4 (the most vulnerable countries), bilateral allocations do so by a lesser extent (30% versus 66%, respectively).

The aim of this study is to determine whether the concave relationship observed in the aggregated data — between vulnerability to climate change and allocation of adaptation finance — holds at the level of the average donor once the analysis accounts for other elements of the donor-recipient relationship. Previous studies and resulting expectations are discussed in the next section.

Figure 3. Total finance allocated by quartile of vulnerability (2010-2015) (OECD 2016; OECD 2019; ND-GAIN 2019)



2.2 Previous research and expectations

There are three main theories typically used in the development literature to explain the provision of aid: first, the provision of aid is altruistic in nature; second, aid is provided in line with donor self-interest; and third, donors consider recipient characteristics that could impact the effectiveness of the provided aid (Alesina and Dollar 2000; Berthélemy and Tichit 2004; Younas 2008).

Most studies of development aid allocation suggest that donors consider recipient need and give more aid to poorer countries (Alesina and Dollar 2000). Climate finance has also shown to be targeted at countries with lower Gross Domestic Product (GDP) per capita and, thus, a higher perceived level of need (Halimanjaya 2015; Robinson and Dornan 2017). Vulnerability to climate change is another important proxy for recipient need included in much of the adaptation finance literature.

However, the impact that vulnerability has on the allocation decisions of donors and the distribution of adaptation finance is disputed. Previous research analysing the status of adaptation in Africa and Asia — at an initiative level — suggests that a higher level of vulnerability is not correlated with a higher number of adaptation projects in a country; many of the most vulnerable nations had the lowest rates of adaptation (Ford et al. 2015). Likewise, Donner et al. (2016) found evidence of an uneven distribution of adaptation finance between countries with similar levels of vulnerability. Barrett (2014), who analysed the allocation of adaptation aid at a subnational level in Malawi, observed that adaptation finance flowed to districts with low socioeconomic — but high physical — vulnerability to climate change. Weiler et al. (2018), however, found that on a per capita basis, bilateral donors allocated more finance to recipient countries that were more vulnerable and poorer, leading them to conclude that recipient need matters. And Remling and Persson (2015) found little evidence to suggest the Adaptation Fund Board prioritizes the most vulnerable countries or communities; their study suggests multilateral donors may be less responsive to recipient need than bilateral donors when it comes to the allocation of adaptation finance.

These seemingly contradictory findings can in some part be explained by the differing opinions on how vulnerability should be defined and therefore modelled (Füssel 2007). In the adaptation literature, vulnerability is most often defined as being a function of exposure, sensitivity and adaptive capacity, as per the Intergovernmental Panel on Climate Change's (IPCC) Fourth Assessment Report. However, how the three elements of vulnerability are represented and incorporated in research is inconsistent (Cardona et al. 2012).[4] For example, Barrett (2014) uses infant mortality as a representation of sensitivity, life expectancy

4 In this context, exposure describes the level of stress placed on society and supporting sectors by climate change, sensitivity refers to the level of dependence that people have on climate sensitive sectors, and adaptive capacity encapsulates the ability of society to adapt and support impacted sectors (Chen et al. 2015).

as a measure of adaptive capacity, and a composite indicator sourced from the Global Climate Change Research Program to represent physical exposure. Weiler et al. (2018) test a range of physical exposure indices in their analysis; for adaptive capacity indicators, they use GDP per capita and the adaptive capacity sub-index from the University of Notre Dame Global Adaptation Initiative (ND-GAIN). Sensitivity, however, is not explicitly included in their model. Similarly, Bagchi et al. (2016) include a physical exposure indicator (the percentage of land in a country below 5 meters of elevation) but include no sensitivity variable because of multicollinearity issues. Under the three-part vulnerability definition (exposure-sensitivity-adaptive capacity), sensitivity or "susceptibility to harm" (IPCC 2014, p. 1775) is a qualifying measure, reflecting the fact that high exposure doesn't necessitate a high level of vulnerability. As such, leaving out the sensitivity variable(s) may affect the coefficient estimates for physical vulnerability and generate omitted variable bias. Weiler et al. (2018) argue that the ND-GAIN exposure and sensitivity scores are strongly correlated and using one or the other variable does not substantively change the results. Regardless, including both sub-indices of vulnerability in a single index, or including another indicator of sensitivity, would fit the analysis better within the conceptual framework outlined in the IPCC's Fourth Assessment Report.

Another explanation for the disconnect sometimes observed between vulnerability and the allocation of adaptation finance is the existence of barriers that limit the ability of the most vulnerable states to access finance. One such barrier observed by Barrett (2014) was the need for recipient districts in Malawi to have pre-existing infrastructure in order to demonstrate to donors their ability to manage funds. Many vulnerable states also lack project implementation and fund management capacity at the national level; the limited ability of such countries to develop commercially viable projects and secure loans is another barrier stopping them from accessing quantities of finance commensurate with their level of need (Robinson and Dornan 2015). Afful-Koomson (2015) found that grant-funded activities, which represented 95% of climate fund allocations in Africa in the study period, were typically small scale and included high transaction costs. To increase finance flows, Afful-Koomson (2015) recommended the diversification of financing mechanisms and the securing of loans. However, as the author acknowledged, to secure loans, projects need to be financially viable and offer secure returns to donors; they need to be "bankable" – a challenge for many vulnerable states.

While recipient need clearly plays a role in donors' aid allocation decisions, research has consistently found that donors are also keenly motivated by their own self-interest. Alesina and Dollar (2000) and Balla and Reinhardt (2008) both found that recipients who are more politically aligned with donors are statistically more likely to receive development aid. The allocation of environmental aid is no different; Hicks et al. (2010) conclude that traditional determinates of donor self-interest — such as UN voting affinity and colonial history — are far stronger predictors of environmental aid allocation than eco-functional variables, such as strong government institutions or a track record of environmental treaty compliance. For adaptation finance specifically, however, the nexus between donor self-interest and recipient need is still somewhat disputed, though there is some support for the primacy of donor self-interest in the literature. Barrett (2014), for example, found the presence of existing aid networks (which reduced donor transaction costs) to be a key determinant of adaptation finance allocation. Similarly, Betzold and Weiler (2016) found that donor-recipient relationships matter; donor consideration of past colonial ties was shown to far outweigh the influence that recipient need has on the probability of selection. In contrast, the results presented by Weiler et al. (2018) suggested that recipient need is at least as strong a determinant of adaptation finance allocation as donor self-interest.

Previous studies also indicate donors allocate more development aid to trade partners and to recipients who import a high percentage of goods that donors have a comparative advantage in producing (Berthélemy and Tichit 2004; Younas 2008). While Hicks et al. (2010) found evidence that donors use environmental aid as a form of export promotion, their results are less clear on how the volume of bilateral trade impacts the allocation of aid. Weiler at al. (2018) and Robinson and Dorner (2015) reached the conclusion that larger trade volumes are associated with an increase in the chance of selection and the quantity of adaptation finance allocated per capita, whereas Bagchi et al. (2016) found no statistical evidence that trade influences the dollar amount donors allocate through bilateral adaptation finance.

Aid effectiveness and recipient merit also impacts the allocation of adaptation finance. The level of political stability and the quality of regulation — both indicators of aid effectiveness — have been shown

to increase climate finance allocation (Robinson and Dornan 2016; Michaelowa and Michaelowa 2012; Halimanjaya 2015). A higher level of government quality (a proxy for the fungibility of aid) has also been shown to impact positively upon the provision of both climate finance and development assistance (Michaelowa and Michaelowa 2012; Clist 2011; Halimanjaya 2015). As discussed by Weiler et al. (2018), the expectation of donor allocation depends on whether the donor's presumed focus is on recipient need or on recipient merit. For example, aid recipients with unstable governments are presumably more vulnerable than those with stable governments; thus, if focused on recipient need, donors should allocate more money to unstable states. But if donors have concerns over the fungibility of aid, and therefore the effectiveness of the aid provided, donors may allocate smaller amounts to less well-governed countries. In such a scenario — one focused on recipient merit — the funds would not be allocated solely in line with recipient need. The same logic presumably holds true when considering how vulnerability impacts adaptation finance allocation; while the most vulnerable states may be the most in need of funding (recipient need), many also lack implementation capacity (recipient merit) – which means donors may be hesitant to finance them. In other words, donors may decide that the funds will be more effective elsewhere, in locales with better project proposals, more secure returns and a longer history of managing funding.

This analysis assumes that the provision of adaptation finance will be a function of each of the categories of determinants discussed in this section: recipient need, donor self-interest and a desire for donors to maximise the impact of every finance dollar allocated. Under this framework, vulnerability to climate change is an indicator of recipient need. Broadly speaking, it is hypothesised that:

H1: The higher the level of need in a recipient country, the more adaptation finance it will be allocated.

H2: At a certain threshold level of recipient vulnerability to climate change, donors will begin to allocate less finance to recipients on average.

H3: The more important a recipient is to a donor (politically, economically, strategically), the more adaptation finance it will be allocated by that donor.

H4: The more effective a donor expects adaptation finance to be in a given country, the more finance that donor will allocate to that country.

3. Data and methods used to explore the research question

3.1 Dependent variable: adaptation finance

The adaptation finance data used in the bilateral study is based on project-level aid data from the OECD Creditor Reporting System (OECD 2016). All Rio-marked (principal and significant) adaptation finance allocated by OECD DAC nations from 2011 to 2015 is used for the bilateral analysis.[5] All developing countries or territories eligible to receive official development assistance are considered as potential recipients in the bilateral model (OECD 2016).[6] Setting the dataset up in this way allows for first stage selection probability to be calculated.

Multilateral and fund climate finance data for the period 2013 to 2015 was sourced from the OECD's recipient perspective climate finance database (OECD 2019). This database does not include bilateral contributions already reported in DAC statistics (OECD 2018). Multilateral outflows are collected from the seven main Multilateral Development Banks, or MDBs (based on their climate-related projects and components designation) and also from climate-specific funds and other multilateral institutions (which classify allocations via the Rio markers). As a result, both the Rio markers and the climate components classification are present in the multilateral dataset. Each fund and MDB has a select set of potential recipients eligible for its funding, as determined by each fund's individual mandate. Similar to the bilateral case, the first stage selection problem for multilaterals can be analysed by structuring the data to reflect the specific set of potential recipients for each multilateral donor.[7]

For the second stage analysis, the share of a donor's annual adaptation budget allocated to a recipient is used as the dependent variable. To construct the dependent variable, I divide the amount of adaptation finance a donor allocated to a recipient in a particular year by the total amount of adaptation finance allocated by that donor to all recipients in that same year. As a result, each donor-recipient-year allocation, aggregated if necessary, is included as an individual observation in the analysis. Dropping zero values is not a concern when log transforming the dependent variable, as the second stage only considers positive amounts of allocated finance.

Previous studies of the determinants of adaptation finance allocation have used either the amount of adaptation finance allocated per capita (Weiler et al. 2018), the percent of the global total amount of adaptation finance allocated in a particular year (Betzold and Weiler 2017) or the total amount of adaptation finance allocated (Bagchi et al. 2016) as the dependent variable. The choice of dependent variable relates to how donors are theorised to allocate aid. Neumayer (2003) argues that it is reasonable to assume that donors have a set budget to allocate and that allocating that aid on a per capita basis would be an administratively burdensome task, requiring care not to exceed or fall short of intended expenditure. Under this framework, per capita aid is an outcome of the allocation process rather than a decision factor.[8] Even if donors do consider per capita amounts when allocating aid, following McGillvray and Oczowski (1992), it is assumed that controlling for population in the regression accounts for the donor's consideration of the per capita amount they are allocating. As a result, in contrast to previous studies, the share of a donor's annual adaptation budget allocated to a recipient is used as the dependent variable in the second stage. Using this dependent variable not only arguably better represents the donor's decision-making process, it treats all donors as equal and doesn't allow the allocation patterns of larger donors to bias results (Hicks et al. 2010). Furthermore, it is intuitively easier to conceptualise the "weight" donors put on different factors influencing allocation by looking at how they distribute shares of their allocable budget, rather than focussing on dollar amounts that inherently have a different value to different donors as a result of their different budget sizes. The disadvantage to this approach is that the relative size of the various donor budgets (and therefore the relative significance of various donors) is not accounted for.

5 As this data is used to track progress against funding targets, this paper analyses the allocation patterns of finance as reported to the OECD CRS. No discounting factor has been applied in addition to that already applied by donors. See Technical Appendix, Section 8.9, for a further discussion.

6 See the Technical Appendix, Section 8.2, for a full list of donors and eligible recipients included in the analysis. Note only donors with more than one observation were included in the analysis.

7 Graphs showing the spread of the data for both the multilateral and bilateral models are included in the Technical Appendix, Section 8.3.

8 This is less true for some multilateral development banks, which have resource allocation rules that calculate the appropriate per capita amount based on factors relating to a recipient's need for aid and their ability to use it, among other things (Carter, 2014). As discussed in the text, any consideration of per capita amounts by donors is addressed by controlling for population in the regression.

3.2 Variables related to recipient need

The ND-GAIN vulnerability sub-index is used as a representation of recipient need in this study. The vulnerability sub-index considers a country's vulnerability to climate change to be a function of exposure, sensitivity and adaptive capacity (Chen et al. 2015).[9]

Vulnerability is expected to positively drive both the selection of recipients and the allocation of adaptation finance in line with previous studies (Barrett 2014). Contrary to previous statistical research, however, it is expected that there will be an inflection point in the vulnerability variable, after which a further increase in vulnerability will reduce the adaptation finance budget share allocated to recipients.

Also included in the analysis is a dummy variable signalling whether a recipient is a member of the Alliance of Small Island States (AOSIS 2016). It is presumed that donors will prioritise funding AOSIS members as a result of their explicit vulnerability to climate change. GDP per capita is an additional indicator of recipient need; it is expected that countries with higher levels of GDP per capita will receive less adaptation finance. GDP per capita can also be thought of as an indicator of adaptive capacity; under either conceptualization the aforementioned relationship holds. GDP per capita data is sourced from The World Bank Databank (2019).

3.3 Variables related to donor self-interest

Dyadic variables related to donor self-interest included in the bilateral component of this study are the distance between a bilateral donor and recipient, the level of bilateral trade between the country pairs, and each recipient's level of political allegiance to a potential donor. The distance between donors, measured in kilometres, was sourced from CEPII's GeoDist database (Mayer and Zignago 2011). Trade data for each year of the study is sourced from the UNCTADstat database (UNCTAD 2016). Total exports, measured in thousands of dollars (annual), were compiled into aggregated annual bilateral trade amounts.[10]

The level of political allegiance between the donor and recipient is captured via an index of UN voting affinity with a range between 0 and 1 and enters the model unchanged (Voeten 2013). The colonial history of recipients, sourced from the ICOW Colonial History Data Set (Hensel 2018), was used to generate a dummy variable signifying whether the donor was the potential recipient's main colonial power. This variable was included because a recipient's colonial history has been shown to be a key determinant of development finance; there is no reason to think that donors would act any differently with respect to adaptation finance (Alesina and Dollar 2000).

Hub scores generated from an analysis of the global trade network for each year of the study are also included. This provides more insight into strategic motivations — from both bilateral and multilateral donors — that are not explicitly obvious in recipient specific or dyadic variables.[11] Bilateral donors are expected to prioritise allocations to trade hubs as a form of export promotion, whereas multilateral donors are expected to prioritise recipients with high hub scores as a means of safeguarding important global trade centers in line with the commercial aspirations of their principal donors (Berthélemy 2006). The calculated hub scores enter the model as standardized values, with a mean of zero and standard deviation of one, to ease interpretation in the analysis.

3.4 Variables related to finance effectiveness and recipient merit

In addition to the vulnerability sub-index, the ND-GAIN Index also incorporates a readiness sub-index which measures the readiness of recipients to make use of investments for adaption action. The readiness sub-index relates to the nature of the in-country business environment (Chen et al. 2015). To produce correct coefficient estimates for vulnerability, a country's vulnerability to climate change must be metered against variables which describe that country's ability to effectively use any allocated finance.

9 The construction of the vulnerability index involves the specification of an emissions scenario. The future climate predictions based on the chosen scenario inform the exposure component of the vulnerability indicator. Donor attitude towards climate change is theorised to play a key role in the relationship between vulnerability and the amount of finance pledged. Donor fixed effects are included in the model as a result.

10 I add 1 to all aggregate bilateral trade amounts before log transforming them to avoid dropping the zero values.

11 Pajek, a network analysis program, was used to compute the network scores for each recipient for each year of the study. See the Technical Appendix, Section 8.4, for a further description of the calculation of hub scores.

Disaggregating the ND-GAIN index's readiness component provides governance, social and economic readiness indicators well suited to this purpose. Governance readiness indicators measure the stability of the society and institutional environment that contributes to investment risks. Social readiness indicators measure social conditions that help society to make efficient and equitable use of investment. And economic readiness indicators measure the investment climate that facilitates mobilizing capital from the private sector (Chen et al. 2015). There are obvious synergies between the readiness variables and GDP per capita; as checks for collinearity raised no immediate alarms[12], both GDP per capita and the readiness components are included in the analysis.

3.5 Controls

The total population of potential recipients is included both as a measure of recipient need and as a way of avoiding large populous nations like India and China dominating the poverty (and potentially other) coefficients (Clist 2009). In line with the findings of Trumbull and Wall (1994) and Tezanos Vázquez (2008), population increases are expected to be associated with an increase in the provision of finance. Population data is sourced from the World Bank Databank (2019). Summary statistics are presented in the Technical Appendix, Section 8.5.

3.6 Modelling approach chosen in this study

When dealing with adaptation finance data, a key issue is that many countries receive no assistance, meaning a significant number of observations are clustered at zero. If ordinary least squares regression (OLS) was used on the whole sample, model estimates would be biased toward zero (Clist 2011). Following the aid allocation literature, I use a two-stage hurdle model (Probit/OLS) to overcome this issue (Weiler et al. 2018; Tezanos 2008; Clist 2011).[13] Using this approach, adaptation finance allocation is conceptualised and modelled as two separate stages; in the first stage donors consider the intensive margin decision (whether to provide finance at all), and in the second stage donors consider the extensive margin decision (how much finance to give). Only positive allocations of adaptation finance are considered in the second stage.

In contrast to previous studies of adaptation finance allocation, allocations from both bilateral and multilateral donors are considered, albeit in separate models. While the selection and allocation processes for multilateral and bilateral donors are functionally the same, the variables which drive the decision process for each category of donor are not altogether congruent. For example, the bilateral analysis includes dyadic variables not applicable in the multilateral context, such as the magnitude of bilateral trade flows between a recipient and a donor. That said, the general modelling approach and model specification presented in this section is applicable to both the bilateral and multilateral analyses.

To control for the possibility of simultaneity and allow for information lags, it is assumed that donors only have access to recipient-specific data in the period following the finance allocation decision; all relevant independent variables are lagged by one year (Balla and Reinhardt 2008). To control for heteroscedasticity, robust standard errors are used. Standard errors clustered at the donor level are also reported. The fixed effect approach was chosen over a random effects model, as it did not appear reasonable, in this context, to assume that the unobserved variables are statistically independent of all the observed variables.[14] The inclusion of donor fixed effects in the model accounts for donors' presumably differing motivations and policy positions in relation to the allocation of adaptation finance. The use of donor fixed effects is especially relevant in the multilateral analysis, where both development banks and funds — two presumably distinct groups of donors — are analysed in the same model. The decision to include time invariant recipient factors, such as colonial history and the distance between donor and recipient, was chosen over a recipient fixed effect approach.

12 All variance inflation factors (VIFs) <5

13 A key assumption with the hurdle model specified is that $Cov\left[\varepsilon_{d,t}^{st.1}, \varepsilon_{d,t}^{st.2}\right] = 0$; see the Technical Appendix, Section 8.6, for a further discussion of estimator choice and related specification tests.

14 A Hausman test supported this decision for both the bilateral and multilateral models.

3.6.1 Model specification

In the first stage, donors select the countries to which they will allocate finance. The selection stage is estimated via equation 1:

$$\text{Probability}(D_{dr,t}=1) = \alpha_0 + \alpha_1(v_{r,t-1}) + \alpha_2(v_{r,t-1})^2 + \alpha_3 X_{r,t-1} + \alpha_4 Y_r + \alpha_5 Z_{dr,t-1} + \delta_{d,t}^{st.1} + \eta_t^{st.1} + \varepsilon_{dr,t}^{st.1} \quad \ldots \text{(eq. 1)}$$

The dependent variable, $\text{Probability}(D_{dr,t}=1)$, is a binary selection variable and is modelled using a Probit regression. $D_{dr,t}=1$ indicates that donor d selected country r as a finance recipient. In the second stage, donors decide what size share of their adaptation finance budget to allocate to each country selected in the first stage.

The determinants of adaptation finance allocation are modelled using the following multivariate regression model:

$$\ln(a_{r,t}^*) = \beta_0 + \beta_1(v_{r,t-1}) + \beta_2(v_{r,t-1})^2 + \beta_3 X_{r,t-1} + \beta_4 Y_r + \beta_5 Z_{dr,t-1} + \delta_{d,t}^{st.2} + \eta_t^{st.2} + \varepsilon_{d,t}^{st.2} \quad \ldots \text{(eq. 2)}$$

Where $\ln(a_{r,t}^*)$ represents the log-transformed share of a donor's adaptation finance budget allocated to a recipient, *r*, in time *t*. In both stages, the key independent variable of interest, a recipient's vulnerability to climate change, is represented by $v_{r,t-1}$. A vulnerability squared term, $(v_{r,t-1})^2$, is included to acknowledge that the most vulnerable countries may not have the highest probability of selection or be allocated the most finance once selected. $X_{r,t}$ is a matrix of time-variant, recipient-specific variables, Y_r is a matrix of time-invariant recipient-specific variables, and $Z_{dr,t}$ is a matrix of time-variant dyadic variables representing the strategic and economic relationship between a donor and recipient. To account for differences in donor policies or in the subjective measurement of the effectiveness that any allocated finance would have on a recipient, donor fixed effects, $\delta_{d,t}$, are included in both stages.[15] The term η_t represents a time effect that is common to all countries within a given year; time-invariant effects of interest could include the general effects of world business cycles or the impact of new global agreements on the provision of climate finance. $\varepsilon_{dr,t}$ are the remaining error terms. While it is expected that the coefficients will differ across the two stages (i.e. $\beta \neq \alpha$), their signs are expected to be the same.

15 See the Technical Appendix, Section 8.7, for a discussion on the validity of using fixed effects in the first stage Probit models.

4. Findings

4.1 Stage 1 results

Table 1 shows the results of five model specifications. Specifications 1, 2 and 3 refer to the bilateral model and specifications 4 and 5 refer to the multilateral model. Time and donor fixed effects are included in all specifications. Specifications 1 and 4 only include vulnerability (lagged) as a linear term, whereas specifications 2, 3 and 5 include a vulnerability (lagged) squared term.

4.1.1 Variables related to recipient need

The independent variables of most interest, vulnerability and vulnerability squared, are significant in specifications 1 and 2, even when standard errors are clustered at the donor level. The negative sign associated with the coefficient of the squared vulnerability variable in specification 2 — coupled with the positive coefficient associated with the linear vulnerability variable — indicates a concave relationship between vulnerability and selection. The absolute difference in magnitude between the two terms plays a key role in determining the location of the extremum of the concave curve. The marginal effect of (lagged) vulnerability on selection for specification 2 is shown in Figure 4.[16] I find that the effect is clearly concave in the bilateral case, with the probability of selection increasing until the vulnerability index is approximately equal to 0.45. The probability of selection then decreases at an increasing rate for the remainder of the range of the variable.[17] As hypothesised (H2), this result shows that while an increase in vulnerability improves the probability of selection up to a point, ultimately bilateral donors are less likely to select the most vulnerable countries as finance recipients.

In the multilateral case, the relationship between vulnerability and selection is significant only in specification 4, where it is negative. When the quadratic vulnerability term is added in the multilateral model, significance of the linear vulnerability term is lost (see specification 5). Like Remling and Persson (2015), who found little evidence to suggest the Adaptation Fund Board prioritised the most vulnerable countries as funding recipients, I find no indication that multilateral donors are more likely to select countries that are most vulnerable to climate change. The calculated marginal effect of (lagged) vulnerability on the probability of selection by a multilateral donor indicates that the least vulnerable nations are approximately 15% more likely to be selected as funding recipients than those most vulnerable to climate change (see Figure 5).

In support for hypothesis H1 — that donors would allocate funds in line with recipient need — the results indicate both bilateral and multilateral donors are less likely to select wealthier countries as adaptation finance recipients. Higher levels of GDP per capita, significant in specifications 1 through 5, are associated with a reduced likelihood of selection across all models. Interestingly, the coefficients for the bilateral model (with the addition of dyadic variables) are more than twice as large as those in the multilateral specifications, suggesting that when it comes to recipient selection, bilateral donors are more responsive than multilateral donors to recipient need. Even when dyadic variables are removed from the bilateral model in specification 3, the coefficient of GDP per capita is still approximately 50% larger than it is in the multilateral specifications. Hicks et al. (2010) similarly found bilateral donors to be more responsive than multilateral donors to a recipient country's global and regional environmental significance, policies and institutions, and poverty level.

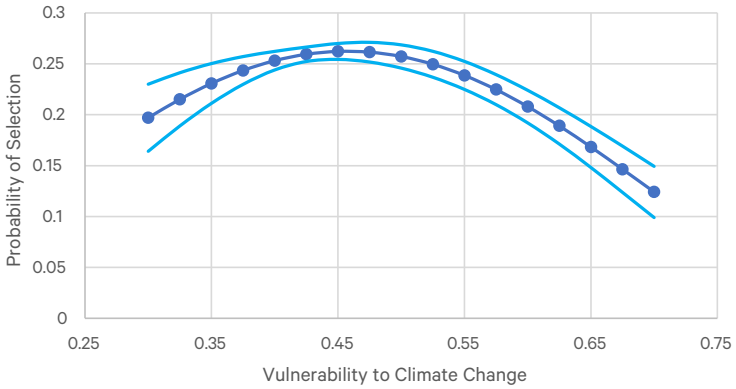
In contrast to expectations, the final recipient need variable included in the model, AOSIS (a dummy variable indicating membership in the Association of Small Island States), is not significant in either the bilateral or multilateral specifications. This suggests small island states are not significantly more likely to be selected as finance recipients by either multilateral or bilateral donors.[18]

16 Specification 2 is plotted, as the coefficients of both vulnerability and vulnerability squared are significant in that model and there is strong evidence that the model is a better fit than specification 1, according to the Akaike information criterion (AIC for Specification 1 is equal to 16879, AIC for Specification 2 is equal to 16863; a linear probability model is fit for the purpose of calculating these values).

17 To allow for the correct calculation of the marginal effects for specification 2, vulnerability squared is included as an interaction term, resulting in the marginal effect of vulnerability and vulnerability squared being combined into one coefficient.

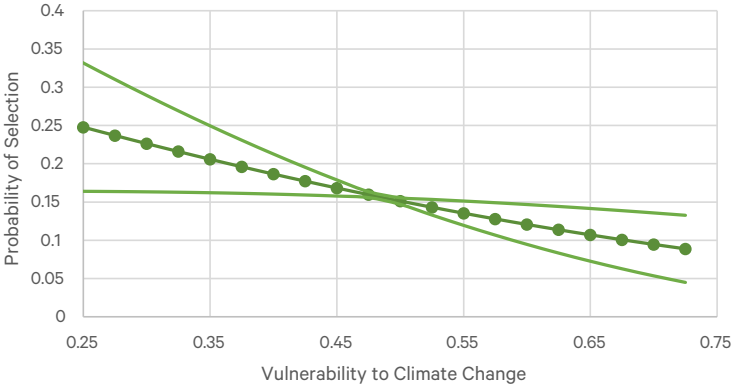
18 Sensitivity testing showed that it is the introduction of the readiness indices that causes the loss in significance.

Figure 4. Bilateral Selection



(Predictive Margins with 95% Confidence Intervals)

Figure 5. Multilateral Selection



(Predictive Margins with 95% Confidence Intervals)

4.1.2 Variables related to donor self-interest

There is a negative coefficient associated with the political alliance proxy (Agree in UN) in specifications 1 and 2. Although not significant when standard errors are clustered at the donor level, this suggests a similar trend to the findings of Hicks et al. (2010), who concluded that a larger share of a donor's environmental aid budget is provided to countries to which the donor is less politically aligned. This is contrary to the expectation that bilateral donors would prioritise political allies, as outlined in H3. It may be that countries vulnerable to climate change vote differently in the United Nations' General Assembly than OECD donor countries because they have fundamentally misaligned goals. Alternatively, since the dependent variable is the share of a donor's aid budget, rather than a dollar amount, realist theories of international relations may be less applicable. As suggested by Hicks et al (2010), when budget shares are considered, the determinants of the funding allocation decisions of larger western governments may be counterbalanced by those of other players whom are less driven by strategic considerations. This may be even more true in the case of adaptation finance; developed countries may feel some responsibility for the predicament of those impacted by climate change, and thus altruistic motives could trump certain political considerations.

The colonial history variable is positive and significant at the 1% level in the bilateral model (specifications 1 and 2), a finding which is robust when clustered standard errors are specified. This result supports H3, and indicates that donors are more likely to select their former colonies as adaptation finance recipients. The coefficient for hub scores (a representation of importance in the global trade network) is negative in specifications 1, 2 and 3 and positive in specifications 4 and 5. The coefficient for hub scores,

however, is only significant in the bilateral model (specifications 1 to 3) with the level of significance in specification 2 dropping when standard errors are clustered at the donor level. These results suggest bilateral donors are less likely to select important global exporters as finance recipients. In the bilateral model, the coefficient of ln(distance) is negative and significant. The negative sign implies that donors are less likely to select recipients who are further away, with distance from the donor being considered a proxy for strategic interests.

4.1.3 Variables related to finance effectiveness and recipient merit

Higher social readiness, an indicator of social conditions that help society to make efficient and equitable use of investment (Chen et al. 2015), is associated with a lower probability of selection in both the bilateral and multilateral models. This result is highly significant in all specifications and indicates that donors associate greater social capacity with less need for adaptation finance. As adaptation to climate change is in many ways a coordination problem, requiring many actors to work together, this result supports the assertion that recipient need is a key indicator of selection for both multilateral and bilateral donors. The coefficient for economic readiness (which measures the ease of doing business), is positive and significant in the bilateral model, indicating a good business environment encourages selection by bilateral donors. This suggests bilateral donors value the investment certainty afforded by a stable and hospitable business environment. Conversely, the coefficient for economic readiness is negative, but not significant, in the multilateral model. The coefficient for governance readiness, expected to increase the likelihood of selection, is positive and significant at the 1% level across all 4 specifications. This provides evidence that donors prioritise allocations in countries where the impact of the provided finance is expected to be most effective (H4). The coefficient of (ln)population is positive and significant at the 1% level in specifications 1 through 4, suggesting both multilateral and bilateral donors provide more funds to more populous nations in line with their presumably greater aggregate level of need.

Table 1. Stage 1: probability of selection as an adaptation finance recipient, all categories of finance considered.

	BILATERAL donors (2011–2015)			MULTILATERAL donors (2013-2015)	
	SPECIFICATIONS				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Dependent Variable: Binary Selection				
Vulnerability lagged	-1.558	12.11	13.03	-1.649	2.628
	(0.243) ***	(1.589) ***	(1.509)***	(0.560)***	(3.314)
	[0.289] ***	[2.290] ***	[2.263]***	[0.697]**	[3.960]
Vulnerability lagged squared		-13.24	-14.19		-4.121
		(1.520) ***	(1.449)***		(3.214)
		[2.210] ***	[2.190]***		[3.928]
ln(GDP per capita lagged)	-0.466	-0.455	-0.374	-0.212	-0.210
	(0.0253) ***	(0.0255) ***	(0.0214)***	(0.0520)***	(0.0522) ***
	[0.0387] ***	[0.0375] ***	[0.0357]***	[0.0560]***	[0.0567]***
Governance readiness lagged	0.920	0.963	1.082	0.917	0.921
	(0.172) ***	(0.175) ***	(0.159)***	(0.387)**	(0.389) **
	[0.325] ***	[0.331] ***	[0.366]***	[0.577]	[0.572]
Social readiness lagged	-1.610	-1.038	-0.584	-0.781	-0.592
	(0.157) ***	(0.172) ***	(0.154)***	(0.318)**	(0.345) *
	[0.276] ***	[0.271] ***	[0.277]**	[0.280]***	[0.213]***
Economic readiness lagged	0.939	0.974	0.789	-0.588	-0.561
	(0.159) ***	(0.162) ***	(0.155)***	(0.380)	(0.381)
	[0.288] ***	[0.290] ***	[0.370]**	[0.361]	[0.356]
ln(Population lagged)	0.230	0.238	0.291	0.123	0.121
	(0.0149) ***	(0.0153) ***	(0.0108)***	(0.0278)***	(0.0278) ***
	[0.0280] ***	[0.0292] ***	[0.0287]***	[0.0341]***	[0.0340]***
AOSIS	0.0718	0.0742	0.0386	0.134	0.134
	(0.0462)	(0.0465)	(0.0444)	(0.107)	(0.107)
	[0.115]	[0.116]	[0.123]	[0.153]	[0.155]
Hub score lagged (std.)	-0.0641	-0.0332	-0.0327	0.0121	0.0274
	(0.0114) ***	(0.0118) ***	(0.0113)***	(0.0465)	(0.0479)
	[0.0173] ***	[0.0182] *	[0.0185]*	[0.0628]	[0.0667]
ln(Bilateral Trade Lagged)	0.0858	0.0774			
	(0.0100) ***	(0.0102) ***			
	[0.0155] ***	[0.0159] ***			
Agree in UN	-0.449	-0.271			
	(0.160) ***	(0.165)			
	[0.379]	[0.384]			
ln(distance)	-0.195	-0.213			
	(0.0282) ***	(0.0284) ***			
	[0.0992] **	[0.101] **			
Colonial History	0.991	1.011			
	(0.0751) ***	(0.0754) ***			
	[0.345] ***	[0.350] ***			
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Donor fixed effects	Yes	Yes	Yes	Yes	Yes
Observations[19]	17,747	17,747	18,452	3161	3161
McFadden's Pseudo R2	0.334	0.338	0.309	0.244	0.245
% Correctly Predicted	83.33	83.45	82.89	91.20	91.22

Note: Stage 1 is estimated using a Probit model.
(Robust standard errors) [Standard errors clustered at the donor level]
*** p<0.01, ** p<0.05, * p<0.1

19 Variations in the number of observations is caused by missing values in certain covariates.

4.2 Stage 2 results

The Stage 2 analysis considers the extensive margin decision, the results of which are presented in Table 2. The arrangement of Table 2 follows that of Table 1, with the first three specifications (6, 7 and 8) referring to the bilateral model and the last two specifications (9 and 10) referring to the multilateral model. Time- and donor-fixed effects are included in all specifications. Specifications 6 and 9 include vulnerability (lagged) as a linear term, whereas specifications 7, 8 and 10 include a vulnerability (lagged) squared term.

4.2.1 Variables related to recipient need

The concave relationship between vulnerability to climate change and selection identified in the Stage 1 bilateral model is mirrored in the allocation patterns of bilateral donors; in specification 6, the coefficient of the linear vulnerability lagged term is positive and significant and the coefficient of the vulnerability lagged squared term is negative and significant. This result provides support for H2, indicating that not only are bilateral donors less likely to select the most vulnerable countries as finance recipients, but once selected, these countries also receive less finance than their less vulnerable neighbours, all else being equal (see Figure 6). This finding confirms previous research by Betzold and Weiler (2017) and Weiler et al. (2018), but only up to a point. Unlike the findings of this analysis, both previous studies found that the most vulnerable receive the most adaptation finance, all else being equal; in other words, they found that an increase in recipients' physical vulnerability increases bilateral donors' per capita allocation of adaptation finance to recipients, linearly.

A key distinction between the two aforementioned studies and this one, aside from the choice of dependent variable, is that this analysis used the ND-GAIN's combined vulnerability index (exposure-sensitivity-adaptive capacity). Betzold and Weiler (2017) and Weiler et al. (2018) include adaptive capacity and exposure (physical vulnerability) separately and negate the sensitivity sub-index from their regressions. There is clear value in splitting the exposure and adaptive capacity terms, as it allows one to observe the influence each component has on a donor's allocation decision. However, excluding the sensitivity variable presumably decreases the accuracy of the coefficient estimate for the exposure sub-index, because the physical vulnerability of a country is no longer metered by its sensitivity to the exposure. While the exposure and sensitivity scores are correlated, the ratio between the two terms differs on a country-by-country basis; this warrants the inclusion of all three components of vulnerability in the analysis from both a theoretical and econometric perspective.

As shown in Figure 6, bilateral donors allocate larger shares of their budgets as a recipient's climate change vulnerability increases, up to the point where (lagged) vulnerability ≈ 0.525. Taking a closer look at the results for specification 2, it can be seen that, on average, bilateral donors allocate a similar share of their annual finance budget — about 0.16% — to the least vulnerable and the most vulnerable. Nations with a (lagged) vulnerability rating of approximately 0.525 receive, on average, the largest finance endowment from bilateral donors, or about 0.37% of a donor's budget. What is immediately striking is how small these percentages are; the vast majority of adaptation finance allocations represent less than 1% of each donor's annual adaptation budget, with 2.7% as the mean budget share of finance allocated. This indicates a high level of dispersion of finance. GDP per capita is also significant at the 1% level across specifications 6 and 7, with the result robust to the clustering of standard errors at the donor level. This is clear evidence that bilateral donors consider recipient need when allocating funding, in line with H1.

Table 2. Stage 2: allocation of adaptation finance, all classifications of finance considered.

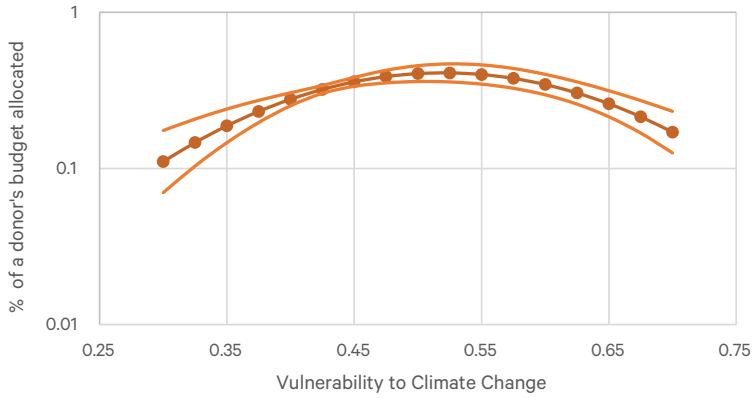
	BILATERAL donors (2011-2015)			MULTILATERAL donors (2013-2015)	
	SPECIFICATIONS				
	(6)	(7)	(8)	(9)	(10)
VARIABLES	Dependent Variable: ln (share of a donor's annual allocation budget)				
Vulnerability lagged	-0.246	28.08	29.43	0.310	9.820
	(0.681)	(4.360) ***	(4.390) ***	(1.667)	(10.76)
	[0.556]	[5.610] ***	[7.019] ***	[1.942]	[11.94]
Vulnerability lagged squared		-27.00	-28.10		-8.995
		(4.063) ***	(4.105) ***		(9.542)
		[5.288] ***	[6.673] ***		[11.00]
ln(GDP per capita lagged)	-0.547	-0.487	-0.468	0.0369	0.0522
	(0.0726) ***	(0.0741) ***	(0.0676) ***	(0.141)	(0.143)
	[0.112] ***	[0.111] ***	[0.0911] ***	[0.111]	[0.107]
Governance readiness lagged	1.058	1.090	0.764	2.315	2.196
	(0.484) **	(0.480) **	(0.463) *	(1.030) **	(1.000) **
	[0.644]	[0.644]	[0.630]	[0.887] **	[0.802] **
Social readiness lagged	-2.456	-1.340	-0.127	0.0619	0.458
	(0.446) ***	(0.478) ***	(0.459)	(0.867)	(1.052)
	[0.534] ***	[0.673] *	[0.751]	[1.093]	[1.283]
Economic readiness lagged	1.079	1.363	1.825	0.00761	0.121
	(0.463) **	(0.459) ***	(0.461) ***	(0.951)	(0.982)
	[0.524] **	[0.512] **	[0.628] ***	[0.989]	[1.030]
ln(Population lagged)	0.263	0.277	0.287	0.291	0.282
	(0.0388) ***	(0.0394) ***	(0.0304) ***	(0.0686) ***	(0.0677) ***
	[0.0933] ***	[0.0913] ***	[0.0818] ***	[0.0974] ***	[0.0934] ***
AOSIS	-0.106	-0.130	-0.0650	0.475	0.473
	(0.146)	(0.146)	(0.146)	(0.288) *	(0.288)
	[0.298]	[0.299]	[0.356]	[0.198] **	[0.200] **
Hub score lagged (std.)	-0.0429	0.0250	0.0345	-0.0726	-0.0353
	(0.0312)	(0.0326)	(0.0307)	(0.102)	(0.113)
	[0.0544]	[0.0519]	[0.0417]	[0.109]	[0.119]
ln(Bilateral Trade Lagged)	0.0845	0.0700			
	(0.0230) ***	(0.0233) ***			
	[0.0337] **	[0.0327] **			
Agree in UN	-0.241	0.0590			
	(0.470)	(0.472)			
	[0.603]	[0.614]			
ln(distance)	-0.733	-0.752			
	(0.0748) ***	(0.0742) ***			
	[0.178] ***	[0.174] ***			
Colonial History	1.508	1.538			
	(0.200) ***	(0.201) ***			
	[0.589] **	[0.609] **			
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Donor fixed effects	Yes	Yes	Yes	Yes	Yes
Observations[20]	4,119	4,119	4,263	493	493
R2	0.287	0.294	0.251	0.236	0.238

Note: Stage 2 is estimated using OLS and considered only positive amounts of finance.
(Robust standard errors) [Standard errors clustered at the donor level]
*** p<0.01, ** p<0.05, * p<0.1

20 Variations in the number of observations is caused by missing values in certain covariates.

As in the bilateral model, the vulnerability lagged squared term is negative in the multilateral model (specification 10). However, the result is not significant — and nor is the other key indicator for recipient need, GDP per capita. Typical indicators of recipient need — such as a recipient's poverty level or its vulnerability to climate change — are not significant determinants of the average multilateral donor's allocation decisions. The results do show, however, that multilateral donors are particularly responsive to one indicator of recipient need in the allocation stage: a recipient's status as an Association of Small Island States (AOSIS) member. Contrary to the bilateral model, AOSIS members are allocated more finance by multilateral donors; the coefficient of AOSIS is positive and significant in specifications 8 and 9, even when clustered standard errors are specified. There is no statistical evidence, however, to indicate that the most vulnerable small island states receive the most funding.

Figure 6. Bilateral Allocation (Predictive Margins with 95% Confidence Intervals)



4.2.2 Variables related to donor self-interest

As expected from a strategic perspective, colonial history is a key determinant of bilateral finance allocation. Bilateral donors allot a budget share to former colonies that is, on average, 5 times larger than the share allotted to other countries (specification 7). Distance also plays a role; a 10% increase in (ln) distance reduces a bilateral donor's budget share allocation by approximately 7%. These results mirror those found in Stage 1 for bilateral donors and support H3: donors prioritise recipients that are of higher strategic importance. Specification 7 also predicts that for a 10% increase in the level of (ln)aggregate bilateral trade shared with a recipient, donors increase the share of their finance budget allocation by 0.67%. This indicates that bilateral donors prioritise trade partners as adaptation finance recipients, as found in the aid literature (Berthélemy and Tichit 2004). The coefficient of (lagged) hub scores, is positive but not significant in any specification. Once again, while positive and in line with expectations (H3), the coefficient of "Agree in UN" is insignificant in specification 7.

4.2.3 Variables related to finance effectiveness and recipient merit

As in Stage 1, the sign of the social readiness coefficient is negative, whereas the sign of the economic readiness coefficient is positive (specifications 6 and 7). The variables are significant at the 10% and 5% level, respectively, in specification 7. These two variables are not significant in any multilateral specification. In specification 7, a 10% increase in social readiness would, on average, decrease bilateral donors' mean budget share of finance allocated to recipients by 12.54%.[21] This result once again provides evidence that bilateral donors target those countries least ready to cope with the impacts of climate change. As predicted in H4, the sign of the coefficient of the governance readiness variable is positive and significant across specifications 5 through 9. The quality of government (a proxy for the fungibility of aid) is a far stronger determinant of multilateral donors' adaptation finance allocation than recipient need, on average. This is most likely a result of multilateral donors strongly associating a higher quality

21 The readiness variables have a range of 0-1.

of government with a reduction in investment risk and an increase in growth potential. Comparing specification 8 (bilateral model) with specification 10 (multilateral model) shows that the coefficient for governance readiness in the multilateral model is approximately 3 times the size of the same coefficient in the equivalent bilateral specification. As in Stage 1, more populous countries are targeted by both bilateral and multilateral donors. A higher population is associated with the allocation of a larger budget share of adaptation finance by both bilateral and multilateral donors. The magnitude of the coefficient is similar in both models. Overall, unlike the findings in Berthélemy (2006), only limited convergence of behaviours among bilateral and multilaterals is observed in the allocation stage.

4.2.4 Comparing different classifications of finance

Table 3 presents four distinct specifications, which evaluate how the vulnerability of recipients drives the allocation of different categorizations of finance. Specifications 11 and 12 consider bilateral allocations classified as significant and principal adaptation finance, respectively. Multilateral allocations of adaptation finance classified as climate components and principal are presented in specifications 13 and 14.

Bilateral donors are observed to allocate larger shares of principal-classified finance than they allocate of significant-classified finance, all else held constant. The relationship between the size of the shares of adaptation finance and the vulnerability of recipients to climate change remains concave and significant in both specifications 11 and 12. Weiler et al. (2018) similarly found that bilateral allocations of principal-classified finance per capita were more responsive to the (physical) vulnerability of recipients than allocations of total (principal and significant) finance.[22]

Specification 14 is unique in Table 3; it is the only specification where the relationship is convex between a recipient's vulnerability and the size of the share it received from a donor's annual adaptation finance budget. The results presented in specification 14 indicate that multilateral donors allocate the largest shares of principal-classified adaptation finance to the most vulnerable states, all else being equal. Conversely, vulnerability is not a significant determinant of multilateral donor's allocations of finance categorised as "climate components/projects". The linear vulnerability term in specification 13 loses significance upon the introduction of clustered standard errors.

Multilateral donors are driven by a specific indicator of recipient need: a recipient's AOSIS status. The coefficient of the AOSIS variable is positive and significant in specifications 13 and 14. A recipient's AOSIS status is only a significant determinant of adaptation finance allocation for multilateral donors; the variable is insignificant in all bilateral specifications in Table 3.

Overall, these results suggest that donors regard recipient need more highly when principal-classified finance is concerned. However, the probability of being selected as a principal finance recipient is lower than the probability of receiving adaptation finance in general. This is largely because principal-classified finance is less common than other categorizations of adaptation finance (Figure 2).

4.2.5 Robustness checks

To test the robustness of the reported results, alternate measurements of adaptation finance allocation were tested using the modelling methodology described in this study. Both ln(adaptation finance allocated per capita) and ln(total allocated adaption finance) were used to replace the ln(share of total adaptation finance allocated) as the dependent variable in the bilateral model. The results, while not reported in the text, were found to be broadly consistent with the findings of this study, as well as with the previous literature (Weiler et al. 2018). Most importantly in relation to this study, the concave relationship observed between vulnerability and the allocation of adaption finance remained statistically significant when the alternate dependent variables were specified. To see further robustness checks and a discussion of the potential limitations of this study, see the Technical Appendix, Sections 8.8 and 8.9 respectively.

22 As measured by the ND-GAIN exposure index.

Table 3. Stage 2: allocation of adaptation finance, exploration of different classifications of adaptation finance.

VARIABLES	BILATERAL		MULTILATERAL	
	SIGNIFICANT	PRINCIPAL	CLIMATE COMPONENTS	PRINCIPAL
	SPECIFICATIONS			
	(11)	(12)	(13)	(14)
	Dependent Variable: ln (share of total adaptation finance)			
Vulnerability lagged	29.56***	22.22***	32.48	-15.82*
	[5.691]	[5.817]	[19.66]	[7.496]
Vulnerability lagged squared	-28.26***	-20.80***	-32.73*	18.12**
	[5.321]	[5.169]	[17.80]	[5.947]
ln(GDP per capita lagged)	-0.586***	-0.210	0.233	0.149
	[0.108]	[0.157]	[0.139]	[0.199]
Governance readiness lagged	0.575	1.152	1.802	1.766*
	[0.606]	[0.784]	[1.064]	[0.895]
Social readiness lagged	-0.691	-1.732**	2.070	-0.595
	[0.657]	[0.829]	[1.165]	[1.896]
Economic readiness lagged	1.468**	1.485***	1.233	0.437
	[0.557]	[0.446]	[1.865]	[1.762]
ln(Population lagged)	0.242**	0.326***	0.453**	0.182
	[0.0899]	[0.0826]	[0.147]	[0.143]
AOSIS	0.0119	-0.0378	0.784*	0.728*
	[0.353]	[0.321]	[0.353]	[0.345]
Hub score lagged (std.)	0.0140	-0.00197	0.015	-0.532
	[0.0562]	[0.0821]	[0.131]	[0.303]
ln(Bilateral Trade Lagged)	0.103***	0.0157		
	[0.0358]	[0.0342]		
Agree in UN	0.409	-0.0210		
	[0.781]	[0.868]		
ln(distance)	-0.714***	-0.597***		
	[0.178]	[0.180]		
Colonial History	1.955***	0.835***		
	[0.559]	[0.267]		
Year fixed effects	Yes	Yes	Yes	Yes
Donor fixed effects	Yes	Yes	Yes	Yes
Observations	3,466	1,969	264	150
R2	0.3062	0.3103	0.3021	0.2491

Note: this table considers a restricted sample, which contains only positive amounts of finance.
Estimated using cluster specific fixed effects.
[Standard errors clustered at the donor level]
*** p<0.01, ** p<0.05, * p<0.1

5. Discussion

This study highlights an apparent disconnect between high levels of vulnerability to climate change and the allocation of adaptation finance by both bilateral and multilateral donors. The results indicate that the most vulnerable countries are the least likely to get selected as adaptation finance recipients by either bilateral or multilateral donors. Confirming the results of Weiler et al. (2018), this study finds that donors are less driven by recipient vulnerability when allocating finance classified as significant (not primarily focused on adaptation) than they are when distributing finance classified as principal (primarily focused on adaptation). The same holds true for the climate components designation used by development banks, which is also less responsive to a recipient's vulnerability to climate change than multilateral principal-classified finance. The divergence in the pattern of allocation of different classifications of finance is not particularly surprising; recipient vulnerability may not enter into donor conversations in cases where adaptation is a significant, but not principal, aim.

These findings come as adaptation finance increases; in 2017, MDB climate finance hit a seven-year high of US$35.2 billion (World Bank 2018). But adaptation finance with a principal climate objective may not be keeping up; in 2016, for the first time, it decreased in volume (OECD 2017). This lends great relevancy to this paper's findings. If principal-classified finance continues to decrease relative to other categorizations of adaptation finance, the most vulnerable states may not benefit in a manner proportionate to the rate of growth of the broader pot of adaptation finance.

Overall, the allocation decisions of bilateral donors are more responsive to recipients' climate change vulnerability than those of multilateral donors. However, principal-classified multilateral adaptation finance — one of the smallest categories of adaptation finance — is the only classification where donors are shown to prioritise the most vulnerable to climate change. Within this category, small island developing states receive larger shares, all else held constant, as found by Robinson and Dornan (2015); however, they are not statistically more likely to be chosen as finance recipients. The most vulnerable members of the Alliance of Small Island States (AOSIS) also do not receive the largest shares of multilateral adaptation finance in general, relative to other AOSIS members. These results indicate that while certain classifications of multilateral adaptation finance fill some of the funding gap left by bilateral donors, overall, there is only limited evidence to suggest that multilateral donors prioritise the countries most vulnerable to climate change. This is contrary to expectations: since bilateral donors are constrained by bilateral relations, the normative assumption is that multilateral donors would be freer to target recipients based on their objective level of need.

Why are the observed trends occurring? As reported in the literature, the most vulnerable states often lack sophisticated capital markets, possess lower levels of private sector activity, have difficulty demonstrating fund management experience, and have a limited ability to develop bankable projects (Barrett 2014; Robinson and Dornan 2015). These are all probable contributors to the observed allocation patterns. The complex application and accreditation processes associated with securing certain multilateral funding likely also plays a role (Afful-Koomson 2015). However, this paper's results cannot attribute culpability to factors that were not included as variables in the model, thanks to measurement and data availability issues. Nonetheless, the allocation patterns described in this study highlight the need for donors to re-evaluate policy positions and design allocation strategies to better ensure that vulnerable states are allocated volumes of finance proportionate to their level of need.

6. Conclusion

In this paper, I explored how both multilateral and bilateral donors distribute climate change adaptation finance. I specifically focused on how and whether a country's vulnerability affects the allocation it receives from donors. In line with the aid allocation literature (e.g. Alesina and Dollar 2000; Younas 2008), bilateral donors were found to allocate more adaptation finance to recipients with a higher level of need (lower GDP per capita), more strategic importance (e.g. with whom they share a larger amount of bilateral trade) and higher levels of good governance (where aid is presumed to be more effective). Multilateral donors were also observed to prioritise well-governed nations.

Previous studies found a positive and linear relationship between vulnerability to climate change and the allocation of bilateral adaptation finance (Betzold and Weiler 2017; Weiler et al. 2018). However, this study shows that this positive relationship only holds up to a point. The relationship between vulnerability and bilateral donors' selection for and allocation of adaptation finance is concave. Furthermore, as found by Remling and Persson (2015), multilateral donors were not observed to prioritise the most vulnerable, on average; they only prioritised vulnerability when allocating principal-classified finance. There is, however, some evidence that multilateral donors target groups vulnerable to climate change, even if they do not prioritise the most vulnerable within those groups. Specifically, multilateral donors were found to allocate more adaptation finance to AOSIS members once they were selected as finance recipients. AOSIS nations, however, are not statistically more likely to be selected.

Overall, the results indicate strong empirical support for the existence of barriers that limit the ability of the most climate vulnerable countries to access a share of adaptation finance proportionate to their level of need. While the exact nature of these barriers cannot be causally inferred from the model, there is a raft of studies that support the assertion that factors such as the fragmentation of the adaptation finance landscape and a limited ability to develop bankable projects are reducing the flow of adaptation finance to vulnerable states (Robinson and Dornan 2015; Afful-Koomson 2015; and Barrett 2014).

Suggestions for further research include linking project-level data to the appropriate component of the disaggregated ND-GAIN vulnerability index (by country sector) to better model donor considerations of vulnerability. This would align each packet of adaptation finance with the specific sectoral vulnerability it purports to be targeting (as opposed to the country-level vulnerability rating), presumably improving the accuracy of the results. The use of more granular data may also help to isolate and identify additional barriers to accessing adaptation finance not observed in a country-level analysis, such as sectoral biases or the influence of funding trends. The disaggregation of funding by type (commercial loan, concessional loan, grant, etc.) would also provide additional insights.

In conclusion, this study shows that vulnerability is only attractive to donors up to a point; on average, the most vulnerable nations are neither the most likely to be selected as adaptation finance recipients or to receive the largest adaptation finance budget shares. The implications of the reported results are twofold. First, an increase in adaptation finance will not necessarily proportionally increase the amount of funding flowing to the most vulnerable; donors, in other words, were not found to allocate all classifications of finance uniformly. Second, as the most vulnerable nations do not receive the largest shares of adaptation finance, the allocation patterns of donors are thus out of sync with the Paris Agreement and the associated goal of prioritising funding for the nations most vulnerable to climate change (UNFCCC 2015).

7. References

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8. Technical Appendix

8.1 Activities that qualify as having a principal focus on adaptation

Activities that qualify for a "principal" score under the climate change adaptation marker include several classes of projects, such as enabling activities and those that have a focus on agriculture, forestry, fisheries, health, energy, coastal zone protection, policy and legislation and water and sanitation.

Examples include:

- **Enabling Activities:** This includes improving weather and climate information systems or supporting the development of climate-change-adaptation-specific policies, programmes and plans.
- **Policy and legislation projects:** Those that would qualify as having a principal focus on climate change adaptation include projects that strengthen the capacity of national institutions, including finance and planning ministries that are responsible for coordinating and planning adaptation activities and for the integration of adaptation into planning and budget processes. Making Disaster Risk Reduction (DRR) information and tools more accessible for climate change adaptation negotiators and managers would also qualify.
- **Water and sanitation:** Efforts to improve water and sanitation include the monitoring and management of hydrological and meteorological data for decision-making on impacts of climate change, as well as strengthening capacity for integrated planning and management of water resources.
- **Forestry and fisheries:** This could include mapping changes in the range of fish species and strengthening the monitoring of fish stocks to determine the impacts of climate change, as well as using natural seed banks and existing plants to restore former forest areas, in order to reduce vulnerability to the impacts of climate change.
- **Health:** This includes developing or enhancing systems for monitoring drinking water, food and air quality, in areas affected by higher temperatures, floods and rising sea level. Projects might also strengthen food safety regulations in areas affected by higher temperatures, notably in terms of microbiological quality, avoidance of contact with pest species, conservation duration and conservation temperatures.
- **Energy:** Projects may include the strengthening of energy transmission and distribution infrastructure to cope with the impacts of climate change, or the design and construction of measures to protect critical energy infrastructure from the impacts of floods and storms.
- **Coastal zone protection:** This includes the conservation of mangroves and coral reefs to protect coastal zones from weather-related catastrophes.

The above information is sourced from the 2011 Handbook on the OECD-DAC climate markers.

8.2 Complete donor and recipient list

Table 4. Complete Donor and Recipient List

Bilateral Donors	Potential Recipients			
Australia	Afghanistan	Fiji	Namibia	Turkmenistan
Austria	Albania	Macedonia	Nauru	Turks and Caicos Islands
Belgium	Algeria	Gabon	Nepal	Tuvalu
Canada	Angola	Gambia	Nicaragua	Uganda
Czech Republic	Anguilla	Georgia	Niger	Ukraine
Denmark	Antigua and Barbuda	Ghana	Nigeria	Uruguay
Finland	Argentina	Grenada	Niue	Uzbekistan
France	Armenia	Guatemala	Oman	Vanuatu
Germany	Azerbaijan	Guinea	Pakistan	Venezuela
Greece	Bahrain	Guinea-Bissau	Palau	Viet Nam
Iceland	Bangladesh	Guyana	Panama	Wallis and Futuna
Ireland	Barbados	Haiti	Papua New Guinea	West Bank and Gaza Strip
Italy	Belarus	Honduras	Paraguay	Yemen
Japan	Belize	India	Peru	Zambia
South Korea	Benin	Indonesia	Philippines	Zimbabwe
Luxembourg	Bhutan	Iran	Rwanda	
Netherlands	Bolivia	Iraq	Saint Helena	
New Zealand	Bosnia and Herzegovina	Jamaica	Saint Kitts and Nevis	
Norway	Botswana	Jordan	Saint Lucia	
Poland	Brazil	Kazakhstan	Saint Vincent and the Grenadines	
Portugal	Burkina Faso	Kenya	Samoa	
Slovak Republic	Burundi	Kiribati	Sao Tome and Principe	
Slovenia	Cabo Verde	Kosovo	Saudi Arabia	
Spain	Cambodia	Kyrgyzstan	Senegal	
Sweden	Cameroon	Lao People's Democratic Republic	Serbia	
Switzerland	Central African Republic	Lebanon	Seychelles	
United Kingdom	Chad	Lesotho	Sierra Leone	
United States	Chile	Liberia	Slovenia	
Multilateral Donors	China (People's Republic of)	Libya	Solomon Islands	
Adaptation Fund	Colombia	Madagascar	Somalia	
African Development Bank	Comoros	Malawi	South Africa	
African Development Fund	Congo	Malaysia	South Sudan	
AsDB Special Funds	Cook Islands	Maldives	Sri Lanka	
Asian Development Bank	Costa Rica	Mali	States Ex-Yugoslavia	
European Bank for Reconstruction and Dev.	Côte d'Ivoire	Malta	Sudan	
European Investment Bank	Croatia	Marshall Islands	Suriname	
GEF General Trust Fund	Cuba	Mauritania	Swaziland	
GEF LDC Trust Fund	Dem. People's Rep. of Korea	Mauritius	Syrian Arab Republic	
GEF Special Climate Change Trust Fund	Dem. Rep. of the Congo	Mayotte	Tajikistan	
IDB Special Fund	Djibouti	Mexico	Tanzania	
Inter-American Development Bank	Dominica	Micronesia	Thailand	
International Bank for Reconstruction and Dev.	Dominican Republic	Moldova	Timor-Leste	
International Development Association	Ecuador	Mongolia	Togo	
International Finance Corporation	Egypt	Montenegro	Tokelau	
International Fund for Agricultural Dev.	El Salvador	Montserrat	Tonga	
Islamic Development Bank	Equatorial Guinea	Morocco	Trinidad and Tobago	
Nordic Development Fund	Eritrea	Mozambique	Tunisia	
Strategic Climate Fund	Ethiopia	Myanmar	Turkey	

8.3 ln(share of allocation) vs. vulnerability

Figure 7. Bilateral Data

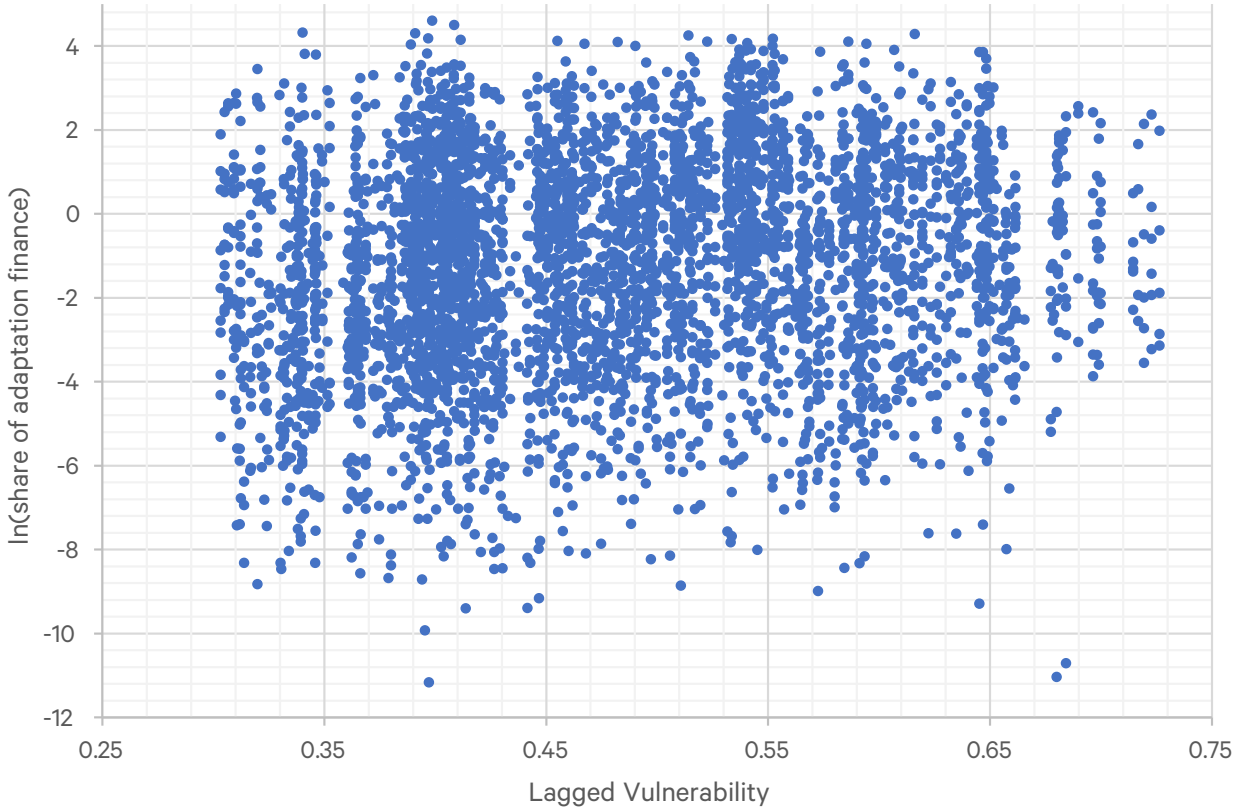
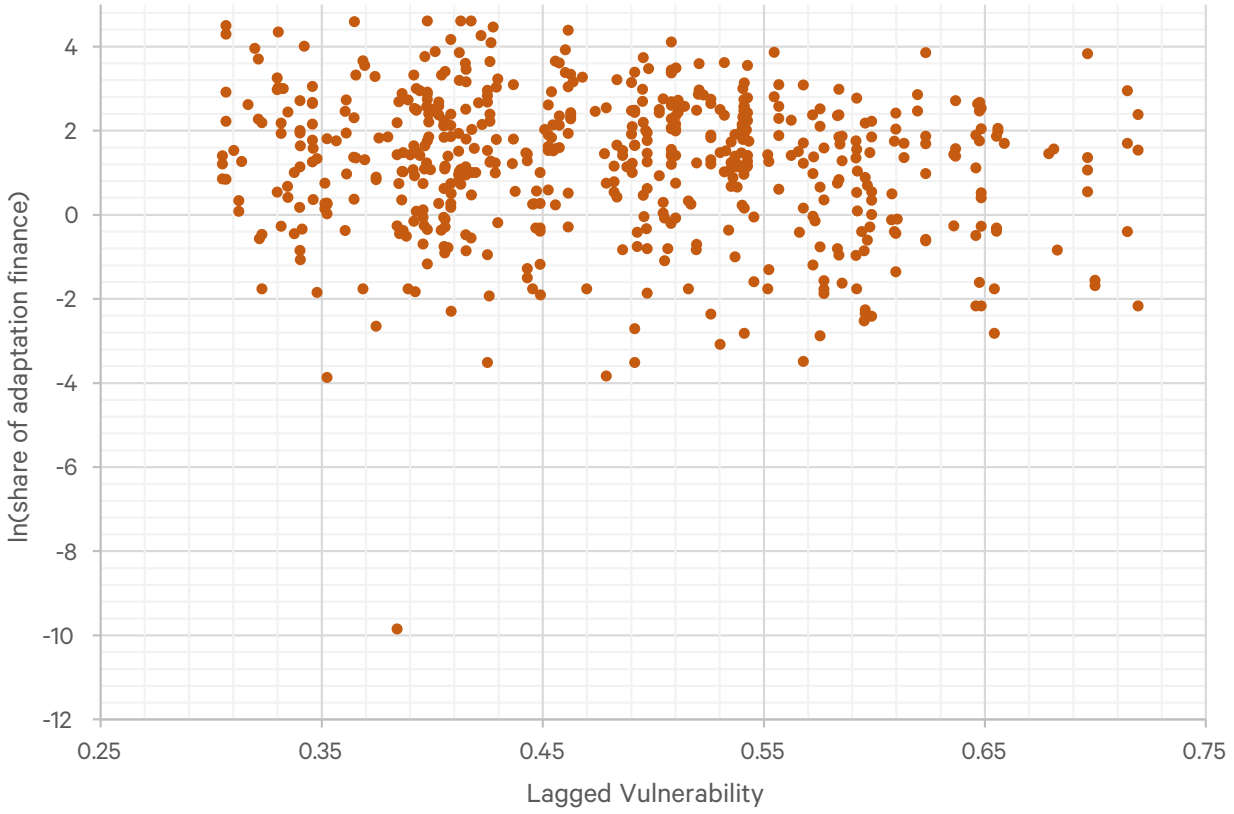


Figure 8. Multilateral Data



8.4 Hub and authority scores

Hub and authority scores, developed by Kleinberg (1999), are a refinement of in-degree and out-degree centrality, which is a simple count of a node's incoming and outgoing network connections, respectively. Hub scores are related to out-degree centrality, and authority scores are related to in-degree centrality. The calculation of hub and authority scores is iterative; a node's hub score is boosted when it is connected to a node that has a high authority score, where a high authority score is attributed to a node that is an important global importer.[23] A node's authority score is improved when it is connected to nodes that have high hub scores, where a high hub score is attributed to a node that is an important global exporter. Even when the total export amounts for nodes are similar and small, different exporters will receive different hub scores dependent on their overall position and centrality in the network. As a result, finance recipient hub scores contain a level of signalling related to the quality, type and demand for the goods that that country exports over and above that which can be inferred from aggregate trade figures. Two countries that export goods with the same aggregate dollar value, but who export those goods to a different subset of countries, will have different hub scores dependent on the number of countries they export to, and the authority scores of those nations. An analysis of the correlation between hub and authority scores negated including both variables in the analysis. As adaptation finance is key to maintaining productive capacity in developing nations, providing a strong link to the export orientated hub scores, the decision was made to include hub scores rather than authority scores. In addition, exports typically make up a significant portion of the economies of developing nations. The raw trade (export) data used in the global trade network analysis was sourced from the UNCTADstat trade database (UNCTADstat, 2016).

23 See Kleinberg (1999) for a discussion of the theory relating to the calculation of hub and authority scores.

8.5 Summary statistics

Table 5. BILATERAL - Descriptive Statistics: Restricted Sample (No Finance Received)

Variables	Mean	SD	Min	Max
Principal finance (US $, Millions, 2014)	0.000	0.000	0.000	0.000
Significant finance (US $, Millions, 2014)	0.000	0.000	0.000	0.000
Lagged vulnerability	0.456	0.102	0.293	0.726
Population	3.370E+07	1.390E+08	5.300E+04	1.370E+09
AOSIS	0.228	0.420	0.000	1.000
GDP per Capita (2011 international $)	10800.090	9952.770	565.595	50283.930
Governance readiness lagged	0.432	0.130	0.122	0.746
Social readiness lagged	0.318	0.127	0.195	0.830
Economic readiness lagged	0.496	0.158	0.021	0.871
Hub score (std.)	0.007	0.994	-0.206	11.691
Bilateral Trade (exports in $'000, annual)	717724.7	8006715.0	0.0	521000000.0
Agree in UN	0.746	0.147	0	1
Distance (km)	7648.346	3921.852	117.345	19629.500
Colonial History	0.016	0.127	0	1

Table 6. BILATERAL - Descriptive Statistics: Restricted Sample (Finance Received)

Variables	Mean	SD	Min	Max
Principal finance (US $, Millions, 2014)	2.515	15.999	0	483.741
Significant finance (US $, Millions, 2014)	5.624	29.192	0	999.469
Lagged vulnerability	0.476	0.095	0.303	0.726
Population	8.090E+07	2.340E+08	5.300E+04	1.370E+09
AOSIS	0.090	0.287	0.000	1.000
GDP per Capita (2011 international $)	6707.391	5611.344	565.595	47829.660
Governance readiness lagged	0.392	0.101	0.122	0.746
Social readiness lagged	0.271	0.113	0.195	0.830
Economic readiness lagged	0.475	0.115	0.021	0.794
Hub score (std.)	0.146	1.408	-0.206	11.691
Bilateral Trade (exports in $'000, annual)	3928526.0	24900000.0	0	559000000.0
Agree in UN	0.708	0.169	0	1
Distance (km)	7911.428	3570.508	394.747	18600.700
Colonial History	0.063	0.244	0	1

Table 7. MULTILATERAL - Descriptive Statistics: Restricted Sample (No Finance Received)

Variables	Mean	SD	Min	Max
Climate Components (US $, Millions, 2014)	0	0	0	0
Principal finance (US $, Millions, 2014)	0	0	0	0
Significant finance (US $, Millions, 2014)	0	0	0	0
Lagged vulnerability	0.461	0.107	0.206	0.726
Population	4.120E+07	1.500E+08	5.300E+04	1.370E+09
AOSIS	0.197	0.398	0.000	1.000
GDP per Capita (2011 international $)	11285.590	14170.460	565.595	132937.700
Governance readiness lagged	0.431	0.142	0.122	0.879
Social readiness lagged	0.319	0.135	0.195	0.942
Economic readiness lagged	0.494	0.171	0.021	0.930
Hub score (std.)	0.027	1.050	-0.305	21.377

Table 8. MULTILATERAL - Descriptive Statistics: Restricted Sample (Finance Received)

Variables	Mean	SD	Min	Max
Climate Components (US $, Millions, 2014)	21.860	60.360	0.000	557.342
Principal finance (US $, Millions, 2014)	4.984	12.522	0.000	101.352
Significant finance (US $, Millions, 2014)	2.174	9.414	0.000	111.468
Lagged Vulnerability	0.480	0.097	0.305	0.719
Population	7.110E+07	2.220E+08	7.234E+04	1.370E+09
AOSIS	0.138	0.345	0.000	1.000
GDP per Capita (2011 international $)	6170.372	5184.402	565.595	25667.550
Governance readiness Lagged	0.396	0.099	0.165	0.742
Social readiness Lagged	0.277	0.122	0.054	0.785
Economic readiness Lagged	0.469	0.105	0.234	0.824
Hub score (std.)	0.040	1.003	-0.305	7.507

8.6 Discussion of alternative estimation methods

There are three main approaches that have been applied in the literature in the context of aid allocation: a two-part model, a Tobit (type 1) model and a Heckman selection model.

The Tobit (type 1) model is designed to be used when a dependent variable is left-hand censored. It can be used in both pooled and panel data contexts. The Tobit (type 1) estimates the chance of censoring at the same time as estimating the value of the variable of interest for the non-censored portion of the data. Typically, the estimation relies on maximum likelihood theory (Clist 2009). A key assumption of the model is that the selection and outcome processes are fundamentally the same. In practice, this means the model restricts the effects of independent variables on the selection and allocation stages to be the same (Hicks et al. 2010). It is not appropriate to use a Tobit (type 1) model in the current setting, as the left-hand censoring point of the adaptation finance data is unknown (i.e. the value at which donors stop earmarking adaptation finance is unknown and presumably differs across donors). Furthermore, while I propose that the selection and allocation stages be estimated using an identical set of variables (I see no reason not to), I do not expect that they will affect the two stages in the same way.

The Heckman, or sample selection model, treats the selection bias as a problem of omitted variable bias (Clist 2009). Unlike the Tobit (type 1) model, it estimates two distinct stages: a selection and allocation stage. It doesn't restrict the effects of the independent variables to remain constant over the two stages. The most problematic assumption of the Heckman model, in the context of this study, is the requirement of an exclusionary variable that has a significant impact upon the first step (selection stage), but not upon the allocation stage. This exclusionary variable is required for separate identification (Hicks et al. 2010; Neumayer 2003). In other words, the identification of the unobserved probability (i.e. the case when selection does not occur) requires that enough information is included in the selection specification regressors such that they are unique with respect to the other parameters in the outcome specification. To correct for selection bias, the Heckman selection model includes the inverse Mills ratio (IMR) in the second stage (OLS). The IMR is equal to the PDF/CDF of the first stage (Probit) model predictions. In the context of this study, it represents the probability that a recipient makes it to the next stage given their characteristics. Neumayer (2003) specifies the total amount of (Arab) aid available per year as an exclusionary variable. As I am considering a panel triad that includes many donors, following this approach is not deemed appropriate given the observed differences in donor budgets. It is further expected that a larger budget would impact the selection decision differently for different donors. Neumayer (2003) questions the validity of the exclusionary variable chosen, stating that "it is not an ideal exclusionary variable since it does not vary across donors, but no better exclusionary variable could be found" (Neumayer 2003, p.10).

The two-part model, alternatively known as a Cragg, Type 2 Tobit, or (double) hurdle model, appears most appropriate for this study as it requires no exclusion restriction and allows the coefficients of the variables to differ across the two stages. A limitation of this approach is that the sample size in the second stage of the model is smaller than if a Tobit or Heckman model were used. This is because the two-stage approach (Probit-OLS) only models the allocation stage for donor/recipient/year combinations, where a positive share of finance is allocated in the second stage (Hicks et al., 2010). As discussed by Halimanjaya (2015), neither normality nor homoscedasticity are a necessary condition for the two-part model to produce stable coefficients (Cameron and Trivedi 2005, pp. 534–538). However, a key assumption of the two-part model, allowing the two stages to be modelled independently, is that $Cov[\varepsilon_{d,t}^{st.1}, \varepsilon_{d,t}^{st.2}] = 0$. In contrast, the Heckman selection model explicitly allows the error terms from both stages of aid allocation to be correlated. While theoretically the validity of the two-part model relies on the assumption that there is no correlation between the error terms of the two stages, in practice the bias resulting from violation of this assumption has been shown to be small (Neumayer 2003 and Manning et al. 1987).

Leung and Yu (1996) suggest that in the absence of an appropriate exclusion variable, it is the level of collinearity between the regressors and the IMR that should determine whether the Heckman selection or Cragg type model should be used. The issue is that in the absence of an appropriate exclusion restriction, separate identification depends upon the non-linearity of the IMR. As the IMR is often an approximately linear function, collinearity can occur, in which case the estimates from the allocation stage would not be robust. Madden (2008) suggests that while what constitutes a high level

of collinearity is debateable, a variance inflation factor (VIF) of greater than 30 would indicate serious issues with the estimator choice.[24]

To evaluate the overall specification of the modelling approach taken, I carry out two tests. Firstly, as a key assumption of a hurdle model is that $Cov[\varepsilon_{d,t}^{st.1}, \varepsilon_{d,t}^{st.2}] = 0$, I test the level of covariance between the Stage 1 and Stage 2 error terms for both models. To do this for the bilateral model, I estimate equation 20 using a Heckman selection model with no exclusion restriction specified (Clist 2009). In the bilateral case, the covariance, Rho, is equal to 0.42 and Prob > chi2 = 0.0012, meaning that independence is rejected, and a key assumption of the two-part model is violated. In the multilateral scenario, using a Heckman selection model[25] results in Rho equal to 0.17 and Prob > chi2 = 0.0939; as in the bilateral case, independence is rejected.

To test the validity of using the Heckman selection model without an appropriate exclusion restriction, the first stage Probit is run for both the bilateral and multilateral models and then the respective IMVs calculated. The calculated IMV is then included in the relevant second stage regression and the corresponding VIF inspected. In the bilateral case, the VIF of the IMV is = 26.2. In the multilateral case, the VIF of the IMV is = 692. As both VIFs are either approaching or in excess of Madden's (2008) proposed threshold collinearity level (VIF=30) and as there is evidence that the bias associated with $Cov[\varepsilon_1, \varepsilon_2] \neq 0$ is small, the two-part model (Probit/OLS) is deemed the appropriate estimator in both cases (Neumayer 2003 and Manning et al. 1987).

24 Belsley et al. (1980) suggest a VIF of 10-100 would indicate issues, with a VIF>30 considered severe.
25 As discussed by Woolridge (2012), in rare cases it makes sense to exclude elements from the selection equation.

8.7 A note on the validity of using fixed effects in the first stage

The incidental parameter problem is typically quoted as the reason why fixed effects can't be used in non-linear models. According to Cameron and Trivedi (2005), the reasoning is as follows: when a dataset consists of a short panel, introducing fixed effects dummies (α1, . . . , αZ) into a non-linear model at the individual level creates issues because each α_i depends on a fixed number of observations defined by the length of the panel. As the number of individuals, Z, increases, so too do the number of incidental parameters, resulting in the incidental parameters being inconsistently estimated as $Z \rightarrow \infty$. The problem is that, in general, this contaminates the estimation of the betas. This is not an issue for the linear model, as there exists many ways to consistently estimate the betas despite the presence of the incidental parameters (i.e. the first differences method).[26]

Following Beck (2015), if the total number of parameters is G + k, the number of observations is NG (where N = group size, G= number of groups, and k = the number of covariates). While it is not advisable to estimate a model where the number of parameters is a sizable fraction of the number of observations (for reasons described by the incidental parameter problem), if N is large enough, the results from a logit model using fixed effects dummies exhibit very little bias.[27] As the fixed effects included in stage one are specified at the donor level, the groups are largely well-balanced and, as the smallest group's size in the first stage is >100 in the bilateral model, specifying fixed effects dummies is not an issue in terms of bias.[28] In the multilateral model, while group size in the first stage is less balanced, the smallest group has 36 observations, with all other group sizes greater than 100.

To test the legitimacy of using a Probit model with fixed effects dummies in the first stage, a comparison of the probability of receiving finance from a bilateral donor (the marginal effects) was calculated using a Linear Probability Model (LPM), Logit, Probit and Heckman Selection model, all with time and donor fixed effects and standard errors clustered at the donor level (Table 9 - akin to specification 2 in Table 1). In the case of the LPM, xtreg is used so the "within" degrees of freedom correction were applied. The similarity in magnitude and sign across the majority of the coefficients suggests no severe bias among the different estimators.

As an aside, using xtlogit with the fixed effects set at the donor/recipient level results in many observations being dropped from the first stage because there is no variance in the outcome for many cases. In addition, such an approach negates the opportunity to look at time-invariant recipient variables that are of interest (i.e. the distance between donor and recipient in the bilateral analysis). In addition, the conditional logit model does not allow computation of marginal effects, which makes the interpretation of the results more difficult.

An additional point worth mentioning is that when fixed effects are added via dummies, the degrees of freedom adjustment for the cluster-robust covariance estimator will be wrong, as the number of regressors used to calculate the adjustment will include the fixed effects dummies (G). This is not an issue in the current research, as the groups are balanced and large in the first (>100 observations per group), meaning that the degrees of freedom adjustment applied to the cluster-robust estimate of the variance matrix is theoretically approximately equal to that which would have been calculated if within estimation had be used.[29]

26 See Cameron and Trivedi (2005, p. 726) for a more in-depth discussion.
27 As discussed by Beck (2015), these results are transferrable to the Probit model. Beck (2015) focuses on the Logit model as he compares including fixed effects dummies with the conditional Logit approach
28 For example, α doesn't increase with N.
29 For example, in the case of the first stage as G is large relative to k, c≈1 for within estimation and c ≈ N/(N-1) ≈ 1 for (LS)DV estimation. See Cameron and Miller (2015) p.331 for more information.

Table 9. Stage 1 estimator comparison – Bilateral Model

	Stage 1 Comparison Dependent Variable: Binary Selection			
Variables	**LPM**	**Logit**	**Heckman**	**Probit**
Vulnerability lagged	-0.0784	-0.0595	-0.0700	-0.0711
	(-1.30)	(-0.79)	(-1.00)	(-1.01)
ln(Bilateral Trade lagged)	0.0106***	0.0154***	0.0157***	0.0156***
	(3.78)	(4.56)	(4.96)	(4.85)
ln(Population lagged)	0.0541***	0.0495***	0.0482***	0.0479***
	(6.21)	(9.29)	(8.90)	(8.65)
AOSIS	0.0352	0.0140	0.0154	0.0149
	(1.70)	(0.60)	(0.66)	(0.64)
Agree in UN	-0.172**	-0.0419	-0.0513	-0.0544
	(-2.35)	(-0.54)	(-0.66)	(-0.70)
ln(distance)	-0.0422*	-0.0400*	-0.0431**	-0.0428**
	(-1.85)	(-1.89)	(-2.10)	(-2.10)
Colonial History	0.291***	0.196***	0.204***	0.203***
	(2.84)	(2.85)	(2.95)	(2.96)
ln(GDP per capita lagged)	-0.0924***	-0.0891***	-0.0915***	-0.0916***
	(-9.14)	(-11.63)	(-12.87)	(-12.75)
Governance readiness lagged	0.336***	0.200***	0.193***	0.194***
	(4.36)	(3.11)	(3.05)	(2.96)
Hub score lagged (std.)	-0.194***	-0.221***	-0.208***	-0.209***
	(-3.16)	(-3.94)	(-3.88)	(-3.83)
Social readiness lagged	0.133*	0.200***	0.194***	0.196***
	(1.96)	(3.30)	(3.35)	(3.31)
Economic readiness lagged	-0.00622	-0.00708**	-0.00691*	-0.00668*
	(-1.43)	(-1.98)	(-1.92)	(-1.84)
N	17747	17747	17747	17747

t statistics in parentheses
* p < .10, ** p < .05, *** p < .01

8.8 Robustness checks

To test the robustness of results across both stages of both models (bilateral and multilateral), standard errors clustered at the donor level were compared with their robust counterparts.[30] Additional regressions not reported in this paper were also run with regional dummy variables added. The coefficients and significance of vulnerability and vulnerability squared — the key independent variables of interest — are stable and remain significant upon the inclusion of regional dummies in all specifications.

As only positive instances of adaptation finance allocation are considered in Stage 2, the donor level clusters, some of which are small, differ in size. This issue is further compounded in the multilateral analyses, where there are fewer observations and years of data and a smaller number of donors. This is a concern, as the rejection rate with unbalanced clusters is much worse than when balanced clusters are considered (Cameron and Miller 2015). To address this issue, the wild cluster bootstrap procedure is used (Cameron and Miller 2015). This procedure eliminates test over-rejection associated with having too few clusters by correcting the standard errors. It holds the regressors fixed across bootstrap replications. This procedure is carried out on specifications 7 and 10. Key to this research is the relationship between vulnerability and the share of finance allocated to each selected recipient. Some changes in the level of significance for certain variables is evident when the wild cluster bootstrap procedure is used as shown in Tables 10 and 11 below.

30 Some cluster-robust standard errors are smaller than the corresponding robust standard errors. This is caused by negative correlation of residuals. Further identification of suitable within-cluster predictors could remove the correlation and improve the model.

Table 10. Comparison of P Values: Specification 7 – Bilateral Model

		Robust Std. Errors	Cluster Robust Std. Errors	Wild Cluster Bootstrap Std. Errors
Variables	**Coefficients**	**P>|t|**	**P>|t|**	**P>|t|**
Vulnerability lagged	28.08	1.33e-10	3.00e-05	0
Vulnerability lagged squared	-27.00	0	2.30e-05	0.00200
ln[GDP per capita lagged]	-0.487	5.75e-11	0.000167	0.00200
Governance readiness lagged	1.090	0.0230	0.102	0.148
Economic readiness lagged	-1.340	0.00508	0.0567	0.0780
Social readiness lagged	1.363	0.00301	0.0129	0.0280
ln[Population lagged]	0.277	0	0.00533	0.0200
AOSIS	-0.130	0.372	0.666	0.722
Hub score lagged [std.]	0.0250	0.444	0.634	0.608
ln(Bilateral Trade Lagged)	0.0700	0.00270	0.0413	0.0580
Agree in UN	0.0590	0.901	0.924	0.952
ln(distance)	-0.752	0	0.000185	0.00200
Colonial History	1.538	0	0.0177	0
Year fixed effects		Yes	Yes	Yes
Donor fixed effects		Yes	Yes	Yes
Observations		4,119	4,119	4,119

Note: t-statistics generated from the wild cluster bootstrap procedure are robust to clustering with a small number of sampling units. 1000 bootstrap iterations computed.

Table 11: Comparison of P Values: Specification 10 – Multilateral Model

		Robust Std. Errors	Cluster Robust Std. Errors	Wild Cluster Bootstrap Std. Errors
Variables	**Coefficients**	**P>|t|**	**P>|t|**	**P>|t|**
Vulnerability lagged	9.820	0.362	0.422	0.424
Vulnerability lagged squared	-8.995	0.346	0.425	0.434
ln[GDP per capita lagged]	0.0522	0.716	0.633	0.642
Governance readiness lagged	2.196	0.0286	0.0140	0.0160
Economic readiness lagged	0.458	0.902	0.908	0.940
Social readiness lagged	0.121	0.664	0.725	0.746
ln[Population lagged]	0.282	3.71e-05	0.00776	0.00600
AOSIS	0.473	0.101	0.0301	0.00200
Hub score lagged [std.]	-0.0353	0.755	0.771	0.864
Year fixed effects		Yes	Yes	Yes
Donor fixed effects		Yes	Yes	Yes
Observations		493	493	493

Note: t-statistics generated from the wild cluster bootstrap procedure are robust to clustering with a small number of sampling units. 1000 bootstrap iterations computed.

The results suggest that the fact that there are few and sometimes small and unbalanced clusters in Stage 2 is impacting the level of significance of my results in certain cases. While no variables completely lose their significance when the wild cluster bootstrap procedure is used, the level of significance of certain variables does change in some cases. This robustness check confirms that the structure of the data in Stage 2 needs to be considered.

To test for multicollinearity, variance inflation factors (VIFs) were analysed after running both stages; all calculated VIFs were less than 5, indicating no immediate concerns related to multicollinearity from an econometric perspective.[31]

8.9 Potential limitations

A limitation of the empirical approach used in this study is the underlying assumption that all potential adaptation projects in a country, in a certain year, are considered for funding using the same vulnerability rating. This is highly contentious given the range of potential adaptation projects that address very different (and sometimes contradictory) issues — for example, water security versus flooding. By aggregating projects into yearly allocations from donor to recipient, this study lacks the level of granularity that would make project specifics observable. As the ND-GAIN vulnerability index considers six sectors in its calculation — food, water, health, ecosystem services, human habitat and infrastructure — it would be possible to match sector vulnerability with project level data. This would be a significant undertaking and was not considered for this research.[32] It is expected that in so doing, the accuracy of results would be improved, since the level of noise in the data would be markedly reduced. There are surely cases where countries have very different levels of vulnerability for each sector. The direction of bias introduced in this study's aggregate approach is dependent on whether the sector the donor is targeting is more or less vulnerable than the level of vulnerability indicated by the overall index.

Data quality and availability are also concerns in this analysis. Some of the insignificant results may be caused by the small number of observations and short timeframe associated with some of the regressions (a particular issue in the multilateral categorical analyses). Furthermore, Ellis and Moarif (2016) argue that there are inconsistencies between what countries "count" as climate finance. This means that national reports of climate finance are not always comparable, complete or consistent. This inaccuracy is expected to increase as donors expand their annual commitments to meet the target of mobilising US$100 billion each year in climate finance, unless a major reform in the reporting of the adaptation marker takes place. In response to the overcoding issue, Weiler et al. (2018) discount significant-classified finance by 50% as a means of engendering more robust results. The approach in this paper was to include all allocation data as reported so as to deduce results representative of the allocation claims of donors. Nonetheless, it must be acknowledged that inaccurate categorization introduces a bias into the analysis. Junghans and Harmeling (2010) found significant evidence for overcoding in the OECD CRS dataset, concluding that 65% of the projects examined were inappropriately coded as they were not found to have adaptation as a significant or principal target as determined by GermanWatch coding standards[33]. If miscoding in the CRS is random, the noise introduced into the data would inflate the calculated standard errors, causing the relative levels of significance reported to drop; however, in so doing, it would also increase the robustness of my results. On the other hand, consistent overcoding by donors would introduce a positive bias.

The Probit regressions carried out in Stage 1 are presumably unbalanced by the large number of small but positive shares of finance, which overinflate the probability of being (meaningfully) selected for finance. The implication is that the magnitude of coefficients and their level of significance may be larger than that which may have been computed if the observations in question were excluded from the analysis. Tezanos (2008) and McGillivray and Oczkowski (1992) discuss the use of a "minimum threshold" of aid recipients to compensate for the limited impact of highly scattered aid allocations, where a certain number of recipients have particularly low shares. This makes sense when considering an individual donor's aid allocation behaviour, as these authors did; however, there is less justification to use this method in the context of a three-way panel, where recipients may be allocated several small packets of finance that add up to a more significant amount. Nonetheless, it is important to consider the implication of the structural elements of the data on the results, especially as selection does not mean significant funding will be received.

31 An LPM model which excluded donor fixed effects was specified for the first stage to allow computation of the VIFs.

32 See Chen et al. (2015) for an overview of each sector included in ND-GAIN's vulnerability index.

33 Junghans and Harmeling (2012) included several examples of overcoded projects, including a water supply improvement project located in Iraq. The project was coded as adaptation however was judged not to be explicitly linked to climate change as the lack of infrastructure and requirement for investment was a result of the security situation rather than a required response to climate change pressures.

SEI Headquarters

Linnégatan 87D Box 24218
104 51 Stockholm Sweden
Tel: +46 8 30 80 44
info@sei.org

Måns Nilsson
Executive Director

SEI Africa

World Agroforestry Centre
United Nations Avenue
Gigiri P.O. Box 30677
Nairobi 00100 Kenya
Tel: +254 20 722 4886
info-Africa@sei.org

Philip Osano
Centre Director

SEI Asia

10th Floor, Kasem Uttayanin Building
254 Chulalongkorn University
Henry Dunant Road, Pathumwan
Bangkok 10330 Thailand
Tel: +66 2 251 4415
info-Asia@sei.org

Niall O'Connor
Centre Director

SEI Tallinn

Arsenal Centre
Erika 14, 10416
Tallinn, Estonia
info-Tallinn@sei.org

Lauri Tammiste
Centre Director

SEI Oxford

Florence House 29 Grove Street
Summertown Oxford
OX2 7JT UK
Tel: +44 1865 42 6316
info-Oxford@sei.org

Ruth Butterfield
Centre Director

SEI US
Main Office

11 Curtis Avenue
Somerville MA 02144-1224 USA
Tel: +1 617 627 3786
info-US@sei.org

Michael Lazarus
Centre Director

SEI US
Davis Office

400 F Street
Davis CA 95616 USA
Tel: +1 530 753 3035

SEI US
Seattle Office

1402 Third Avenue Suite 900
Seattle WA 98101 USA
Tel: +1 206 547 4000

SEI York

University of York
Heslington York
YO10 5DD UK
Tel: +44 1904 32 2897
info-York@sei.org

Lisa Emberson
Centre Director

SEI Latin America

Calle 71 # 11–10
Oficina 801
Bogota Colombia
Tel: +57 1 6355319
info-LatinAmerica@sei.org

David Purkey
Centre Director

SEI Stockholm Environment Institute

sei.org

@SEIresearch @SEIclimate