UNIVERSITY OF GOTHENBURG
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Master's Thesis in Economics

Being vulnerable; it's attractive to a point

An exploration of the major determinants of climate change adaptation finance allocation

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Abstract

I study the major determinants of climate change adaptation finance allocation. Both the intensive margin decision and the extensive margin decision are considered. All adaptation finance allocations made by OECD Development Assistance Committee nations to eligible developing countries or territories since 2011 are considered. Using a two-step hurdle model to explore the determinants of both selection for and allocation of adaptation finance, I find evidence against donor coordination and strong support for a concave relationship between the vulnerability of countries to climate change and their probability of selection as an adaptation finance recipient. This concave relationship is also present in the second stage of the model which estimates the allocation patterns of donors. This finding is in contrast to a previous study by Betzold and Weiler (2016) which found a strictly positive relationship between vulnerability and the probability of selection. My results suggest that an overall increase in bilateral climate finance should not be expected to impact upon all at risk nations to the same degree. The observed selection and allocation patterns indicate that on average, the nations most vulnerable to climate change are less likely to be selected as finance recipients. In addition, when selected, those most vulnerable tend to receive less finance than their less vulnerable neighbours.

KEYWORDS: *climate change, vulnerability, finance, aid, two-step hurdle model*

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1. Introduction

Climate change is expected to impact upon the basic elements of life for people around the world (Stern, 2007). Health outcomes, food production and access to water will all be affected. Entire island nations are at risk of disappearing before the turn of the century (Locke, 2009). Over the last decade, the amount of official development assistance (ODA) earmarked as climate finance has increased rapidly. However, most bilateral and multilateral climate portfolios target mitigation; there is a recognised need to increase adaptation finance (Atteridge, 2016 and OECD, 2008).

As opposed to climate change mitigation, which focuses on actions geared towards curtailing carbon emissions and limiting temperature rise, climate change adaptation efforts aim to moderate harm or to exploit beneficial opportunities (Bernstien et al., 2007). A key distinction between mitigation and adaptation is that climate change mitigation is a global public good and climate change adaptation is a regional (or private) good designed to ameliorate impacts whose timeline of materialisation is not well defined (Michaelowa and Michaelowa 2011).

At the fifteenth session of the Conference of the Parties (COP 15) held in Copenhagen in 2009, developed countries committed to jointly raise 100bn USD a year in climate finance by 2020 for climate action in developing countries (UNFCCC, 2009). With such significant amounts of climate finance being mobilised, there is clear opportunity to reduce the impact of climate change on those most vulnerable. For this to occur, the money needs to flow to those whom are most at risk. A sound understanding of the determinants of adaptation finance allocation is required to inform policy design such that it guides the money to where it needs to be. As the allocation of environmental aid has been shown to be integral in securing developing country participation in environmental agreements, there may be more on the table than just money; global consensus around climate action may in part hinge on funding allocation decisions (Hicks et al, 2010). The key research question that this study assesses is therefore:

What are the major determinants of climate change adaptation finance allocation?

To what extent adaptation finance is distributed related to recipient need, donor self-interest or the subjective effectiveness of the provided finance has significant implications for developing countries reliant on funding to reduce their climate vulnerabilities. A fact especially pertinent for countries particularly vulnerable to the impacts of climate change such as small island developing states.

Variables that have been shown to affect donor decisions regarding poverty aid allocation can be split into three main categories; political and strategic determinants related to donor self-interest, indicators representative of recipient need, and finally, recipient characteristics expected to impact on the effectiveness of the provided aid (Alesina and Dollar, 2000; Berthélemy and Tichit, 2004; Younas, 2008). Whilst the theoretical underpinnings defining the provision of poverty aid and climate change adaptation finance are arguably the same, the determinants of receiving funding related to adaptation are presumed to be different to those which define the provision of poverty aid. This is because the primary impetus behind the provision of climate adaptation finance, and environmental aid more generally, is typically not to alleviate immediate suffering or to boost economic growth.

Dudley and Montmarquette's (1976) model of individual donor optimisation forms the theoretical basis used to analyse climate finance allocation in this paper. The model assumes that the objective of each donor is to maximize its utility, which is a function of the subjectively measured impact of the aid provided on the well-being of the recipient nation's residents. A key component of the current research is the extension of the model to incorporate Expected Utility Theory (EUT). In so doing, I analyse how uncertainty regarding the manifestation of climate change induced events during the donor designated funding period (relevant to the projects donors are considering funding) effects the donor decision making process.

I use Rio marked Organisation for Economic Co-operation and Development (OECD) data which includes both grant and loan funding earmarked as having a significant or principal focus on climate change adaptation. [1] All data between 2011 and 2015 is considered. Previous studies have examined the political-economic determinants of adaptation aid from a donor perspective, as well as looked at the determinants of recipient selection for adaptation finance, to the best of the author's knowledge, this study is the first of its kind to look at the determinants of climate change adaptation aid allocation using a two-step approach on a donor/recipient/year panel triad. I make a clear contribution to the literature by developing a theoretical framework well suited to analysing the allocation of climate finance. To provide further insight into the donor decision making process, network analysis techniques are used to explore donor coordination and the use of adaptation finance to further strategic trade alliances.

[1] Four Rio markers exist to track activities targeting the Rio convention objectives; two markers for climate change on adaptation and mitigation, one for biodiversity, and one for desertification (OECD; 2016). See Appendix 1 for an in-depth description of the adaptation marker.

Using a two-part hurdle model, which considers both the intensive margin decision (whether to provide finance at all) and the extensive margin decision (how much to finance to give), I find evidence against donor coordination and strong support for a concave relationship between the vulnerability of countries to climate change and their probability of selection as an adaptation finance recipient. This concave relationship is also present in the second stage of the model which describes the allocation patterns of donors. The analysis shows that the most vulnerable countries are not only less likely to be selected as finance recipients, when selected, they receive less finance than their less vulnerable counterparts on average.

The rest of the thesis is structured as follows; Section 2 provides an overview of relevant literature to both aid allocation, network theory and environmental aid; Section 3 presents the developed theory and outlines the hypotheses; Section 4 describes the data and variables of interest and Section 5 discusses the empirical strategy. The results are presented in Section 6 with the discussion and conclusion included in Sections 7 and 8 respectively.

2. Background and Literature Review

Three strands of literature are especially relevant to this thesis. The first is the development aid literature, especially that which explores the determinants of recipient selection and donor allocation of development aid. The second is the environmental aid literature which provides insight into key drivers of the donor decision making process when the focus is shifted from development to the environment. The third strand of literature relevant to this study is that focused on the use of network analysis to explore aid allocation. I discuss each strand of the literature in more detail below.

2.1. Review of the relevant development aid literature

There are three main arguments presented in the literature regarding the provision of aid; firstly, that the provision of aid is altruistic in nature, secondly that aid is provided in line with donor self-interest, and finally that aid is provisioned based upon the excepted effectiveness that the provided funds will have. More recently, the provision of foreign aid has also been explored as a function of rewarding global ties (Swiss, 2017). The motivations of allocating climate change adaptation finance are expected to fall within the same categories.

Typical political/strategic determinants of poverty aid referenced in the literature include past colonial ties, existing trade relationships and geo-political importance. Previous studies have indicated that donors allocate more aid to trade partners (Berthélemy and Tichit, 2004) and are more likely to allocate aid to recipients who import a high percentage of goods in which donors have a comparative advantage in producing (Younas, 2008). Equally important are donor considerations regarding the subjective impact that their aid will have; the expected fungibility of aid is directly related to the effectiveness of the finance provided and has been shown to impact upon the provision of development assistance (Younas, 2008). Fungibility in the foreign aid context refers to recipients' ability to circumvent donor-imposed restrictions and spend some amount of targeted aid on unintended areas. Typical indicators of aid effectiveness include measures of political stability, level of democracy and regulatory quality (Michaelowa and Michaelowa, 2011 & Halimanjaya, 2015). Recipient need is often defined by poverty/income statistics or access rates to essential goods and services. Recipient characteristics which have been shown to influence aid allocation include the existence of democratic systems, the gross domestic product (GDP) per capita in recipient nations and state fragility (Berthélemy and Tichit, 2004, Neumayer, 2003, Younas, 2008).

Dudley and Montmarquette (1976) pioneered the use of theoretical models to explain donor's aid allocation decisions with their model of individual donor optimisation. Their model, which forms the methodological basis used to analyse climate finance allocation in this paper, consists of two stages; a selection stage and an allocation stage. Since the publication of Dudley and Montmarquette's (1976) seminal paper, many extensions and adaptations of the model have been proposed. Trumball and Wall (1994) extended Dudley and Montmarquette's (1976) model of individual donor optimisation to one of simultaneous optimisation by multiple donors. They assume that donor funds are pooled, and allocation decisions are made by a representative donor at each time period. A key limitation of Trumball and Wall's (1994) extension is the aforementioned constraint that all recipients are weighted the same. An alternate model arrangement developed by Tarp et al. (1999), is to use an eligibility index to model the first stage. In this set up, donors select a subset of potential recipients that they deem most attractive. Tezanos (2008), referring to an attraction index rather than an eligibility index, uses this approach to explore the determinants of Spanish development aid using a two-part model. Using an attraction index doesn't constrain recipient weights to be identical and eloquently allows the empirical approach to be derived directly from the theory. This introduces a greater flexibility into the model; it is for this reason that Tarp et al.'s (1999) model extension forms an important part of the framework used to explore adaptation finance in this paper.

2.2. Environmental aid allocation

Modes of analysis for environmental aid have followed the precedent set in the development aid literature with regards to estimator selection and categories of explanatory variables. As a case in point, in line with the approach taken in much of the development literature, Hicks et al. (2010) employed a modified Cragg model (Probit/OLS) to analyse the determinants of environmental aid allocation using a donor/recipient/year panel triad. Hicks et al. (2010) found that national income, population size, UN voting affinity, and colonial history are far stronger predictors of aid allocation than recipient need. Interestingly, certain explanatory variables have been shown to impact upon the allocation of environmental aid opposite to that which might have been predicted by the development literature. A potential reason for this is that recipient need is no longer solely a function of poverty and/or development indicators. In contrast to the aid allocation literature, Hicks et al. (2010) concluded that a larger share of a donor's environmental aid budget is provided by donors to countries to which they are less politically aligned. Studies have shown that environmental aid, like aid in general, is used by donors to further their own self-interest (Barrett, 2014; Betzold and Weiler, 2016; Hicks et al., 2010). Michaelowa and Michaelowa (2011) explored the relationship between donor characteristics and the likelihood of finance being provided. They found that the ratification of key global environmental agreements and the composition of donor governments positively impacted upon the size of donor countries' climate change adaptation finance budget. The logic here being that increased awareness of climate change related issues and a higher percentage of green preferences within donor countries ups the provision of climate change adaptation related aid.

Studies focused specifically on climate change mitigation finance have theorised that the level and quality of natural capital in a country would impact upon the amount of mitigation finance received. The reasoning behind this assertion is that it is the natural environment (for example marine environments and forested areas) that has the potential to attenuate carbon. Similarly, to Hicks et al. (2010), Halimanjaya (2015) used a two-part (logit/OLS) hurdle model when considering the determinants of climate mitigation finance. Halimanjaya (2015) hypothesised that a country possessing a larger carbon sink would attract more mitigation funding finding that developing countries with higher CO2 intensity, larger carbon sinks, lower per capita GDP and good governance were more likely to receive climate mitigation funding. The use of marine protected areas as a representation of a carbon sink is sound, however, the conclusion that a higher coverage of marine protected areas would attract more mitigation funding through the 'carbon sink' channel appears misconstrued. Whilst marine protected areas are indeed effective carbon abatement zones (Mcleod et al., 2011), the argument that a donor interested in increasing carbon mitigation would invest in a country with high amounts of protected marine areas, unless those areas were at risk, appears flawed. Rather, a logical argument for the positive and statistically significant relationship shown by the authors would be that the marine protected areas variable is a proxy for environmental quality; it would be in the interest of donors who are concerned about the effectiveness of their mitigation financing to invest in a country where the natural environment is of a perceived higher quality and as such more effective at attenuating carbon.

2.3. Aid allocation and network analysis

Network analysis has been increasingly used in assessments of aid allocation. Two studies which are of particular relevance to the current research are those by Betzold and Weiler (2016) and Swiss (2017). Key concepts relevant to network analysis are network centrality and node degree. A node's degree is the measure of the number of connections or edges the node has to other nodes in the network. Network centrality is a measure of the importance of that node in the network. The most straightforward measure of network centrality is a node's in-degree and out-degree centrality which is a simple count of incoming and outgoing network connections respectively.

In the context of the two-stage selection/allocation framework previously discussed, Betzold and Weiler's (2016) study focused on the first stage selection problem; 'what makes donors select countries as finance recipients?' By considering the in-degree centrality of recipient nodes Betzold and Weiler (2016) found evidence that donor coordination is taking place. They also found that as the out-degree centrality of donors increased, the likelihood of donors creating an additional network tie decreased. To capture donor coordination dynamics impacting upon climate change adaptation finance allocation, Betzold and Weiler (2016) used temporal exponential random graph models which capture both the network dynamic in each year as well as cross-temporal correlations. In their analysis, the selection of a country as an adaptation aid recipient constituted the creation of a network tie. The authors considered both forces related to the donor tendency towards coordination and the potentially conflicting desire for donors to use aid to further their own self interests.

Swiss (2017) used count data to calculate recipient node in-degree centrality (related to the number of incoming ties) and recipient node out-degree centrality in the world-society network (related to the number of human rights treaties ratified by each country). Using a fixed effects negative-binomial panel regression of aid network centrality (dependent variable) to examine how aid is allocated, Swiss (2017) found that independent of how much aid countries receive in dollar terms, countries with a higher level of engagement on the global stage can expect a higher degree of aid network centrality. In other words, countries with more global ties receive aid from more donors. In so doing, Swiss (2017) effectively showed that the nature of recipient selection is more complex than realist and humanitarian perspectives can explain. In the same study, Swiss (2017) found that an increase in world society ties held by developing countries did not contribute to higher levels of overall aid funding. This result sits more comfortably in the humanitarian perspective regarding aid allocation; holding all else constant, donors, alignment to global norms does not constitute greater need, in fact it may do the opposite. Whilst Swiss (2017) did consider the allocation stage in their analysis, the focus of the paper was the conceptualisation of recipient selection for aid allocation as a network tie. The use of network analysis as applied by Swiss (2017) provided certain interesting insights as discussed, however focussing on recipient node's out-degree centrality in the global tie network negates some information pertinent to donor strategic thinking. Undoubtedly, the ratification of certain treaties would be looked upon more favourably by donors than others; the use of out-degree centrality scores negates this fact.

Hub and authority scores, developed by Kleinberg (1999), are a refinement of input and output degree. Hub scores are comparable to out-degree centrality and authority scores are comparable to in-degree centrality. A good hub is a network node that points to many good authorities; a good authority is a node that is pointed to by many good hubs. In a trade network analysis, high hub scores would be associated with countries that are good exporters and high authority scores with countries that are good importers. In the context of a global trade network, hub scores reflect aspects of the quality and importance of the goods exported not just the overall quantity. By being weighted with regards to the global importance of the various importers, information related to the regional importance of nodes is also included in the hub score. In this way, the network scores can be thought of as trade indices. Whilst more research would need to be conducted to indicate the specific drivers behind the various scores, including hub scores from a network analysis of global trade in the current study allows for consideration of the strategic aspirations of donors with respect to trade, and doesn't limit the analysis to the bilateral trade connection between a donor and recipient or the recipient's overall trade volume.

3. Theoretical Framework and Hypotheses

To account for the impact of uncertainty on the donor decision making process in the context of the current research, Dudley and Montmarquette's (1976) model is extended to include the concept of donor regret. This allows the uncertainty which surrounds the occurrence of climate change induced events to be considered as part of the donor's selection and allocation decisions. This extension forms the basis of the analysis of donors' allocation decision in the second stage.

I assume that donors experience regret in the case where they choose not to provide finance to a recipient and a climate change induced event occurs which negatively impacts upon that country in the donor defined funding period (in theory this is free to vary for each donor, and for each funded project). When conceptualising regret there are three key elements to consider, first that regret (and the potential utility generated from selecting a recipient) is a function of the probability of a climate change induced event occurring in the funding period. Secondly, that the regret a donor feels is not perceived to be a function of provided finance[2]. Finally, in a scenario where a donor regrets their allocation decision(s), the amount of finance that would have been provided to a recipient is unobservable. To include the potential for donor regret in the first stage, the donors' selection decision is modelled using an attraction index, Λ_{dr}, which measures the interest that donor d has for recipient r.[3] The attraction index is directly related to the donor's utility function but is not necessarily congruent to it. A key point of difference is that the level of regret a donor could feel by not funding a recipient would *increase* the attractiveness of funding that recipient precisely because it would impact *negatively* on the donor's utility function.

3.1. The first stage: recipient selection

During the selection stage, donors vet potential recipients by considering the potential impact that providing finance to each donor could have on the residents of that country and on their own strategic interests. Λ_{dr}, is a function of P_r, the probability of a climate change induced event that causes the recipient's vulnerability to climate change to manifest itself in a given time period *t.* Equation 1 outlines the attractiveness of recipient *r* to donor *d*.

$$\Lambda_{drt} = e^{w_r}[P_{rt}(B(i_{rt} + s_{drt} - z_{rt}) + z_{rt}) + (1 - P_{rt})(Bs_{drt})]$$

$$\therefore \Lambda_{drt} = e^{w_r}\left[P_{rt}\left(Bi_{rt} + z_{rt}(1 - B)\right) + Bs_{drt}\right] \quad \text{... (eq. 1)}$$

$$B = 1 \; if \; a_{rt} > 0; \; B = 0 \; if \; a_{rt} = 0; \; 0 \leq w_r \leq 1$$

Where e is the base of the natural logarithim, w_r are recipient weights and B is a selection indicator dependent on the value of a_{rt}, the share of the donor's adaptation aid budget allocated to each recipient in stage two. It is assumed that each donor can approximate the regret they would feel by not selecting a specific recipient based on that recipient's set of individual attributes. i_{rt} represents the potential impact that any provided finance would have on a recipient and s_{drt} represents the strategic interests of donors. z_{rt} is the regret donors would feel

[2] Rather, it is a function of the potential impact that any amount of finance would have had
[3] This approach is based on the that taken by Tarp et al. (1999), Tezanos (2008) and Tezanos and Guiterrez (2014)

in the case where no climate finance was provided to a country in which a climate change event occurred during the (donor specified) funding period *t*. The subset of recipient weights included in w_r reflect the importance of a recipient in the eyes of donors.

As s_{drt} includes dyadic variables, the relative importance of a given recipient varies for each donor. As a result, the model takes a hybrid approach bridging the gap between an aggregate aid analysis and a focus on an individual donor. Donors estimate the attraction index for each potential recipient, rank them and then apply the following selection rule: if $F_{drt} = 1$, country *r* is selected as a finance recipient by donor *d* as shown below in equation 2.

$$F_{drt} = 1 \text{ if } \Lambda_{drt} \geq A_{dt};\ F_{drt} = 0 \text{ if } \Lambda_{drt} < A_{dt}$$

$$\mathrm{Prob}(F_{drt} = 1) = \mathrm{Prob}\big(\Lambda_{drt} \geq A_{dt}\big) = \mathrm{Prob}\big(\Lambda_{drt} - A_{dt} \geq 0\big)\,; 0 < A_{dt} < \infty \quad \ldots\ (\mathrm{eq.}\,2)$$

$$r = 1, 2, \ldots, Z;\ d = 1, 2, \ldots, D;\ t = 1, 2, \ldots, T$$

A_{dt} is the donor *d*'s predetermined threshold level of attraction at time *t*. Each donor has their own preferences towards the dispersion of their finance budget amongst the potential recipients as indicated by parameter A_{dt}. A larger value of A_{dt} indicates a donor with an aversion towards dispersion; as A_{dt} increases towards ∞, the probability that a country would be selected as a recipient decreases. Conversely, as A_{dt} approaches 0, the donor's level of dispersion of finance and the probability of a country being chosen as a finance recipient increases. Given the setup of the attraction index (eq. 1), an increase in a potential recipient's impact or regret function increases their likelihood of being selected as a finance recipient. Additionally, an increase in the strategic interest a donor has in a recipient, s_{dr}, will also increase the likelihood of a country being selected as a finance recipient. More specifically I find that:

$$\frac{\partial \Lambda_{drt}}{\partial i_{rt}} > 0;\ \frac{\partial \Lambda_{drt}}{\partial z_{rt}} > 0;\ and\ \frac{\partial \Lambda_{drt}}{\partial s_{drt}} > 0 \qquad \ldots\ (\mathrm{eq.}\,3)$$

The relationships discussed above can be understood by analysing the role of probabilities in the attraction index[4]. As Λ_{dr} is dependent on both the probability of a climate change induced event occurring in the funding period and whether or not the donor selects that recipient as a finance recipient, Λ_r has four different aggregate states as shown overleaf in equation 4.

[4] See Appendix 2 for a comment on the assumptions associated with incorporating EUT into the model.

$$\Lambda_{drt} \begin{cases} e^{w_r}(i_{rt} + s_{drt}) & with\, probability\ (P_r)\ when\ \ a_{rt} > 0 \\ e^{w_r}(s_{drt}) & with\, probability\ (1 - P_r)\ when\ a_{rt} > 0 \\ e^{w_r}(z_{rt}) & with\, probability\ (P_r)\ when\ \ a_{rt} = 0 \\ 0 & with\, probability\ \ (1 - P_r)\ when\ \ a_{rt} = 0 \end{cases} \quad \text{... (eq. 4)}$$

As shown above, an increase in the regret function would increase the disutility of not providing finance. To understand how this impacts donor decision making in practice, the case where the donor must select a finance recipient from a set of two recipients n and m will be considered in example 1.

Example 1: For simplicity, suppose that n and m are weighted equally by a donor d, who has a set budget to allocate. The donor can thus choose to allocate funding to either n or m, or both n and m.

First, I will consider whether the donor would select either n or m exclusively. Assuming the prospect of funding m is more attractive for the donor, the decision to select only recipient m would be incentive compatible for the donor if:

$$P_{mt}(i_{mt}) + s_{dmt} - P_{nt}(z_{nt}) \geq A_{dt} > P_{nt}(i_{nt}) + s_{dnt} - P_{mt}(z_{mt}) \quad \text{... (eq. 5)}$$

Now suppose that $P_{nt}(z_{nt})$ is sufficiently large such that the attractiveness of selecting only recipient *m* no longer exceeds the donor's threshold level of attraction:

$$A_{dt} > P_{mt}(i_{mt}) + s_{dmt} - P_{nt}(z_{nt}) > P_{nt}(i_{nt}) + s_{dnt} - P_{mt}(z_{mt}) \quad \text{... (eq. 6)}$$

In this scenario neither n nor m would be attractive enough to be selected as a sole recipient. However, the donor could still consider selecting both n and m. In so doing, the donor would consider the overall attractiveness of the selection proposition; $\Lambda_{proposition} = (\Lambda_{dm} + \Lambda_{dn})/x_d$ where $x_{dt}$is the number of or recipients selected by recipient *d* in period *t* which in this case is equal to two. The donor would choose to fund both recipients if the attractiveness of funding both n and m exceeded A_{dt} and the attractiveness of funding either recipient exclusively as shown below in see eq.8.

$$[P_{mt}(i_{mt}) + s_{dmt} + P_{nt}(i_{nt}) + s_{dnt}]\big/_{x_{dt}}$$
$$\geq A_{dt} > P_{mt}(i_{mt}) + s_{dmt} - P_{nt}(z_{nt}) > P_{nt}(i_{nt}) + s_{dnt} - P_{mt}(z_{mt}) \quad \text{... (eq. 7)}$$

In this example, as it is assumed the donor has a set budget to allocate, the donor's maximization problem could have 3 discrete outcomes; select only recipient n, select both recipients, or select only recipient m.[5] The regret associated with not selecting one recipient impacts upon the attractiveness of selecting the other. This implies that if the degree to which the donor is attracted to n and m is similar, the more attractive proposition for the donor would be to select both recipients rather than to select one over another as articulated in proposition 1 below.

Proposition 1: Donors will spread their adaptation finance budget over many recipients in order to maximise their overall utility, and to avoid the disutility associated with favouring one similarly attractive recipient over another during the selection stage.

Proof: For simplicity, it is assumed that $A_{dt} = 0$, and that the donor has the same level of strategic interest in both potential recipients; $s_{dmt} = s_{dnt} = 0$. The regret a donor feels from not selecting a country as a finance recipient in the case where a climate change induced event occurs in that country in time period *t* is set at equal to 10% of the potential for impact that any amount of provided finance would have had; $z_{rt} = (0.1 * i_{rt})$. Subbing these assumptions into equation 7 and rearranging yields the following inequality:

$$P_{mt}(i_{mt}) - P_{nt}(0.1 * i_{nt}) > {[P_{mt}(i_{mt}) + P_{nt}(i_{nt})]}/{2}$$

$$P_{mt}(i_{mt}) - 0.2P_{nt}(i_{nt}) > P_{nt}(i_{nt})$$

$$P_{mt}(i_{mt}) > 1.2P_{nt}(i_{nt}) \quad \ldots \text{ (eq. 8)}$$

Therefore, $P_{mt}(i_{mt})$ would have to be more than 20% larger than $P_{nt}(i_{nt})$ for the donor to exclusively select m over both m and n. As this result holds for $s_{dmt} = s_{dnt} = 0$ it would hold for all $s_{dmt} = s_{dnt}$, and by continuity for $s_{dmt} \cong s_{dnt}$. See Appendix 3 for a graphical representation of this result.

Ultimately, the dispersion level of a donor's finances being a function of A_{dt}, the number of recipients being funded, x_{dt}, and each potential recipient's individual characteristics which impact upon the values of their respective i_{rt}, z_{rt} *and* s_{drt} functions; the functional forms of which are discussed in conjunction with the exploration of the second stage of the model. It must be noted that whilst the variables included in the aforementioned functions remain the same across the two stages of the model, they are not constrained to impact upon each stage in the same way. Furthermore, the first stage is not a function of the amount of finance provided.

[5] Funding being provided in the case where the resulting attraction index $> A_t$

To make this distinction clear, in the first stage lowercase letters are used to specify the functional forms. In the second stage, uppercase letters are used. For example, $I_{rt} = i_r a_r$ where a_r is equal to the share of a donor's adaptation budget allocated to recipient *r* in stage two. The regret function, z_r, is only a component of the first stage selection decision, and therefore doesn't appear in the second stage of the model.

3.2. The second stage: finance allocation

Once a donor decides on their subset of recipients, they optimise the provision of their budget based on the subjectively measured impact of the finance they provide on the well-being of the recipient nations' residents. In addition, they consider the extent to which their provision of finance forwards their own strategic interests[6]. Separability is assumed between how the donor determines the size of their aid budget, and how they allocate it. Each donor maximises the overall utility derived from the subjective impact of their aid, H, subject to the finance budget constraint represented by $\sum_{r=1}^{R} a_{rt} = 1$.[7] Ignoring time scripts, H can be expressed mathematically as shown below:

$$H = \sum_{r=1}^{R} w_r h_r = \sum_{r=1}^{R} w_r h_r \left(P_r, I_r, S_{dr}\right) \quad \dots \text{(eq. 9)}$$

h_r is a function transforming the subjectively measured impact of the share of a donor's adaptation finance budget, a_r , allocated to recipient *r* (r = 1, 2, …, R) into utility. I_r transforms the subjective impact that any amount of provided finance has on a recipient into utility. Similarly, S_{dr} transforms the impact that the provided finance has on the strategic interests of donors into utility. w_r are a set of weights which characterise the importance of a recipient to a donor and P_r is the probability of a climate change induced event manifesting itself in the funding period *t*. Equation 9 can therefore be rewritten as:

$$\sum_{r=1}^{R} w_r E[h_r|P_r] = \sum_{r=1}^{R} w_r \left(E[I_r + S_{dr}|P_r]\right) \quad \dots \text{(eq. 10)}$$

[6] In contrast to the approach of Trumball and Wall (1994) it is not assumed that all donors pool their aid budget and that a representative donor decides how much is to be allocated to each recipient every year; the perspective is that of the single donor. Thus, dyadic variables are included more intuitively.

[7] In line with the work of Hicks et al. (2010) and Neumayer (2003), it is believed that specifying the amount of aid a country receives as a share of the total amount of aid allocated by a donor as the dependent variable is preferable to using the per capita amount of aid allocated to a recipient. Neumayer (2003) argues that by specifying the dependent variable in this way, all donors are treated as equal and the model will describe the average behaviour of a donor (Hicks et al., 2010).

Expanding equation 10 yields:

$$w_r E[I_r + S_{dr}|P_r] = w_r[P_r(I_r + S_{dr}) + (1 - P_r)(I_r + S_{dr})] \quad \ldots \text{ (eq. 11)}$$

$$\text{Where} \quad \frac{\partial h_r}{\partial I_r} > 0 \; and \; \frac{\partial h_r}{\partial S_{dr}} > 0$$

In equation 11, $(1 - P_r)$ represents the probability of a climate change induced event that causes the recipient's vulnerability to climate change to manifest itself *not* occurring in a given time period. I_r = 0 if a climate change event does not occur within the expected timeframe. As a result, equation 11 can be rewritten as:

$$w_r E[I_r + S_{dr}|P_r] = w_r \; [P_r(I_r + S_{dr}) + (1 - P_r)(S_{dr})] \quad \ldots \text{ (eq. 12)}$$

$$\text{Where} \quad \frac{\partial H}{\partial a_r} = w_r \; [P_r(I_r) + S_{dr}]$$

Proposition 2: Assuming $i_r \approx s_{dr}$, for any given $P_r < 1,$ the difference between the contribution of the impact function and the strategic interests function to the donor's utility will increase as a_r increases. As a result, donors will prioritise countries in which they have a higher level of strategic interest as a_r increases.

Proof: Disregarding recipient weights, w_r, and assuming $P_n = 0.8$ and i_n= s_{dn}=1 where $I_n = (i_n a_n)$ and $S_{dn} = (s_{dn} a_n)$

$$E[I_n + S_{dn}|P_n] = 0.8(I_n + S_{dn}) + (1 - 0.8)(S_{dn})$$

$$= 0.8(i_n a_n) + (s_{dn} a_n) \ldots \text{ (eq. 13)}$$

For a_n=1, the donor ultimately derives 0.8 units of utility from I_n and 1 unit from S_{dn} which amounts to a difference of 0.2 units. If a_n=10, the difference between the utility generated from I_n and S_{dn} is now 2 units of utility. In the current example, as a_n increases the difference in the effective contribution of I_n and S_{dn} to the donor's utility function also increases.

The functional forms of I_r and S_{dr} are discussed below. The impact of the allocated finance on each recipient, I_r, is considered relative to the recipient's GDP per capita, y_r and weighted by the recipient's population, n_r . The subjectively measured impact of the allocated finance is a function of the vulnerability of the recipient to climate change, v_r , the quality of government in the recipient nation, g_i and the indegree centrality of the recipient node in the global adaptation finance network, x_r . The impact and regret functions are formulated as follows[8]:

$$I_r = i_r a_r^{\gamma} = n_r^{\alpha} \left(\frac{v_r^{\theta} g_r^{\chi} x_r^{\iota}}{y_r^{\delta}} \right) a_r^{\gamma} \qquad \dots \text{ (eq. 14)}$$

$$0 \leq \alpha \leq 1,\ 0 \leq \theta \leq 1,\ 0 \leq \chi \leq 1,\ 0 \leq \iota < 1, 0 \leq \delta \leq 1, 0 \leq \gamma < 1$$

All variable weights are constrained between 0 and 1 to allow for the possibility of diminishing returns. If γ were to equal 1, there would be constant returns to scale and no reason why a donor wouldn't prioritise a single donor over all others. a_r is equal to the share of donor d' s (d = 1, 2, …, D) adaptation finance budget allocated to recipient r (r = 1, 2, …, R). Given that vulnerability is an arguably the best indicator of recipient need in this context, and therefore a clear indicator of the potential impact of any provided funds, a higher level of vulnerability would increase the subjective utility donors gain through the allocation of finance (i.e. $\frac{\partial I_r}{\partial v_r} > 0$). As rational actors, donors would prioritise poorer nations as they have less capacity to respond meaning the subjective impact of provided finance would be greater (i.e. $\frac{\partial I_r}{\partial y_r} < 0$). Donors would also seek out countries with higher indegree centrality, a measure which can be considered a community sanctioned signal of legitimate need (i.e. $\frac{\partial I_r}{\partial x_r} > 0$).

The strategic interests of donors are represented by S_{dr} which is a function transforming the perceived impact of donor allocated adaptation finance on the strategic relationship between the donor and recipient into utility. S_{dr} is a function of both trade connections (t_{dr}), trade aspirations (hub_r)and political elements (p_{dr}) such that:

$$S_{dr} = s_{dr} a_r^{\gamma} = \left(\frac{p_{dr}^{\omega} t_{dr}^{\sigma} hub_r^{\varphi}}{x_r^{\tau}} \right) a_r^{\gamma} \qquad \dots \text{ (eq. 15)}$$

$$0 \leq \omega \leq 1,\ 0 \leq \sigma \leq 1,\ 0 \leq \varphi \leq 1,\ 0 \leq \tau \leq 1, 0 \leq \gamma < 1$$

As before, all variable weights are constrained between 0 and 1 to allow for the possibility of diminishing returns and x_r represents the indegree centrality of the recipient node in the global adaptation finance network.

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[8]The donor regret function is assumed to take the same functional form: $z_r = \mathrm{n}_r^{\xi} \left(v_r^{\kappa} g_r^{\zeta} x_r^{\varsigma} / y_r^{\upsilon} \right)$

As shown by Alesina and Dollar (2000) and Balla and Reinhardt (2008) recipients who are more politically aligned with donors are expected to be more likely to receive adaptation finance. It is therefore expected that $\frac{\partial S_{dr}}{\partial p_{dr}} > 0$. Furthermore, a donor is expected to generate more utility by targeting recipients with whom they have higher trade connections or those they consider would be optimal trading partners such that $\frac{\partial S_{dr}}{\partial t_{dr}} > 0$ and $\frac{\partial S}{\partial hub_r} > 0$[9]. Another expected outcome is that the indegree centrality of the recipient node in the global adaptation finance network, x_r , will reduce the strategic interest of a donor in a recipient (i.e. $\frac{\partial S_{dr}}{\partial x_r} < 0$) This result is expected as the clout a donor has over a recipient is presumed to decrease as the number of other (third party) donors increases.

Subbing equations 14 and 15 into 12 allows the total impact of climate adaptation finance as the sum of the impact on identical residents of a recipient country to be expressed as:

$$H = \sum_{r=1}^{Z} w_r a_r^{\gamma} \left[(P_r) \left(n_r^{\alpha} \left(\frac{v_r^{\theta} g_r^{\chi} x_r^{\iota}}{y_r^{\delta}} \right) + \left(\frac{p_{dr}^{\omega} t_{dr}^{\sigma} hub_r^{\varphi}}{x_r^{\tau}} \right) \right) + (1 - P_r) \left(\frac{p_{dr}^{\omega} t_{dr}^{\sigma} hub_r^{\varphi}}{x_r^{\tau}} \right) \right] \quad \ldots \text{(eq. 16)}$$

$$0 \le \alpha \le 1,\ 0 \le \theta \le 1,\ 0 \le \chi \le 1,\ 0 \le \iota < 1,\ 0 \le \delta \le 1,\ 0 \le \omega \le 1,\ 0 \le \sigma \le 1,\ 0 \le \varphi \le 1,\ 0 \le \tau \le 1, 0 \le \gamma < 1$$

As discussed, the amount of climate change adaptation finance allocable at time *t* is determined by the budget constraint:

$$\sum_{r=1}^{R} a_r = 1 \qquad \ldots \text{(eq. 17)}$$

The maximisation problem can therefore be written as follows:

$$\max H = \sum_{r=1}^{R} w_r h_r \left(P_r, I_r, S_{dr}\right) \ s.t. \ \sum_{r=1}^{R} a_r = 1 \qquad \ldots \text{(eq. 18)}$$

Setting up the Lagrangian and deriving first order conditions yields:

$$L = \sum_{i=1}^{m} w_r\, a_r^{\gamma} \left[(P_r) \left(n_r^{\alpha} \left(\frac{v_r^{\theta} g_r^{\chi} x_r^{\iota}}{y_r^{\delta}} \right) + \left(\frac{p_{dr}^{\omega} t_{dr}^{\sigma} hub_r^{\varphi}}{x_r^{\tau}} \right) \right) + (1 - P_r) \left(\frac{p_{dr}^{\omega} t_{dr}^{\sigma} hub_r^{\varphi}}{x_r^{\tau}} \right) \right] + \lambda \left(1 - \sum_{i=1}^{m} a_r \right) \qquad \ldots \text{(eq. 19)}$$

[9] In the context of this study, key global exporters are given a higher hub_r score; the construction of this variable is discussed in section 2.3

$$\frac{\partial L}{\partial a_r^{\gamma}} = \gamma w_r \, a_r^{\gamma-1} \left[\left(P_r n_r^{\alpha} \left(\frac{v_r^{\theta} g_r^{\chi} x_r^{\iota}}{y_r^{\delta}} \right) \right) + \left(\frac{p_{dr}^{\omega} t_{dr}^{\sigma} hub_r^{\varphi}}{x_r^{\tau}} \right) \right] - \lambda = 0 \qquad \ldots (\text{eq. } 20)$$

$$\frac{\partial L}{\partial \lambda} = 1 - \sum_{i=1}^{m} a_r = 0 \qquad \ldots (\text{eq. } 20)$$

Therefore λ, the marginal impact of aid, is equal to:

$$\therefore \lambda = a_r^{\gamma-1} \frac{\gamma w_r \left[(x_r^{\tau} P_r n_r^{\alpha} v_r^{\theta} g_i^{\chi} x_r^{\iota}) + \left(y_r^{\delta} p_{dr}^{\omega} t_{dr}^{\sigma} hub_r^{\varphi} \right) \right]}{y_r^{\delta} x_r^{\tau}}$$

$$and \sum_{i=1}^{m} a_r = 1 \qquad \ldots (\text{eq. } 21)$$

Solving for a_r^*, the optimum share of climate finance to allocate to recipient r, yields:

$$a_r^* = \left[\frac{\gamma w_r \left(P_r n_r^{\alpha} v_r^{\theta} g_i^{\chi} x_r^{\iota+\tau} + y_r^{\delta} p_{dr}^{\omega} t_{dr}^{\sigma} hub_r^{\varphi} \right)}{\lambda y_r^{\delta} x_r^{\tau}} \right]^{\frac{1}{1-\gamma}} \qquad \ldots \ (\text{eq. } 22)$$

Proposition 3: Ceteris paribus, an increase in P_r increases the share of funds received by a recipient

Example 2: This result can be understood in a stylised sense as follows; consider the case where a donor is contemplating whether to fund an adaptation project aimed at addressing a potential recipient nation's capital city's vulnerability to flooding caused by a specific category of storm event. In the past, such a storm was only likely to occur every 20 years, however, according to the specified climate scenario, such a storm would now be considered a 1 in 10-year event. This means that there is now a 10% probability that the storm would occur within a given year. A higher probability of an event occurring reduces the scaling effect that P_r has on the utility function. It must be noted however that the scaling effect that P_r has on the utility function of the donor is highly dependent on the donor determined funding time period[10]. In a less formalised sense, the probability term encapsulates the donor's uncertainty about the specific weather event or phenomenon that is linked to the project being considered for funding.

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[10] To explore the validity of this outcome would require categorisation of individual projects; a task which is beyond the scope of this the current research.

3.3. Hypotheses

This section provides a summary of the expected hypotheses derived from the presented theory. Broadly speaking, the hypotheses presented in this section can be summarised into two categories; those related to the perceived impact of the provided finance on the recipients of the target country, and those related to donor self-interest. First and foremost is consideration of the impact function, the primary driver of which is recipient need. Intuitively, in the context of adaptation finance allocation, climate change vulnerability is directly related to recipient need. Both the impact function and the regret function increase as the vulnerability of that country to climate change increases. However, as shown in eq. 22, the probability associated with a climate change induced event occurring distorts the impact of the recipient's vulnerability on the donor's utility equation[11]. The vulnerability of a nation to climate change is compounded by poverty, which limits a country's capacity to respond to climate change impacts as discussed by Betzold and Weiler (2016). Following this logic, the following hypotheses are made:

H1.1: The lower the GDP per capita of a recipient country, the more likely it is to be selected as a finance recipient and the more adaptation finance it will receive

H1.2: The higher the vulnerability of the recipient nation to climate change, the more likely it is to be selected as a finance recipient and the more adaptation finance it will receive

Equally important to the subjective impact that donors expect their finance will have is the expected fungibility of aid which directly impacts upon the effectiveness of the finance provided. Higher levels of government quality (a proxy for the fungibility of aid) has been shown to impact positively upon the provision of development assistance (Michaelowa and Michaelowa, 2011 & Halimanjaya, 2015). Therefore:

H1.3: Countries with a higher governance readiness index will have a higher probability for selection as a finance recipient and will attract more adaptation finance

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. The positive relationship is expected as climate change impacts are non-discriminatory and affect all members of a country, albeit with a variable severity of impact determined by individual

[11] Intuition related to the impact of probability on the decisions of donors can't be tested directly due to the combination of multiple projects into annual amounts. This constitutes the collapsing of many projects, each focussed on addressing a different vulnerability with a different likelihood of manifestation, into an aggregated representative sum.

specific characteristics. Whilst some contrasting findings have been found regarding the impact of population on aid allocation[12], the relationship is hypothesised to be positive:

H1.4: The larger the population of a recipient country, the more likely it is to be selected as a finance recipient and the more adaptation finance it will receive

As discussed, the second category of hypotheses are those related to the strategic interests of donors. Alesina and Dollar (2000) and Balla and Reinhardt (2008) showed that recipients who are politically aligned with donors are statistically more likely to receive aid leading to the following hypothesis:

H2.1: Aid allocation is politically motivated; countries which are more politically aligned to donor nations will be more likely to be selected as a finance recipients and will receive more adaptation finance

H2.2: Countries which are ex-colonies of the donor nation will be more likely to be selected as a finance recipient and will receive more adaptation finance

As donors use adaptation finance as a form of export promotion (Hicks et al. 2010), the relative importance of finance recipients as trade partners will impact upon the amount of finance they receive such that:

H2.3: The higher the level of bilateral trade between a donor and potential recipient, the more likely it will be that the donor selects that country as a recipient and subsequently allocates them a larger proportion of their adaptation finance budget.

In addition, a donor's finance allocation decision is impacted upon by a desire to secure trade with important global export hubs. As discussed in section 3.2, a higher hub score, hub_r , is attributed to nations which are important global exporters, therefore I hypothesise that:

H2.4: Countries with higher recipient hub scores will attract more adaptation finance

As a recipient's indegree centrality in the aid network, x_r , is included in both I_r and S_{dr} it is unclear whether a higher level of recipient node indegree centrality would encourage or discourage donor selection and subsequent finance allocation. There are two schools of thought, the first being related to Chong and Gradstein's (2008) `free rider hypothesis': If aid is about relieving vulnerability to climate change, donors can free-ride on the donations of others which

[12] Younas (2008) found a negative relationship between population and the provision of aid

suggests that each donor would provide less aid as the number of donors giving to a particular recipient increases (represented by the inclusion of , x_r .in S_{dr}). Alternatively, donors may capitalise on information constraints and thus value recipients whom other donors deem worthy of finance more highly (represented by the inclusion of , x_r .in I_r); historically the trend has been towards dispersion, as such it is hypothesised that:

H2.5: Higher indegree centrality in the aid network will lead to an increased likelihood of selection

Finally, in line with proposition 2 it is hypothesised that:

H2.6: The strategic interests of donors will become more important for donors (relative to recipient need) as the share/value of their finance packets increase.

4. Variables, Data Sources and Data Generating Processes

To test the above hypotheses, I use a variety of data sources. The main source is the Organisation for Economic Cooperation and Development's (OECD) creditor reporting system (CRS) which includes all earmarked adaptation finance allocated by OECD Development Assistance Committee (DAC) nations since 2011 (OECD, 2016). There are five years of suitable data available from 2011 onwards.[13]. The CRS data used includes all developing countries or territories eligible to receive official development assistance as potential recipients (OECD, 2016). [14] I also have information on the vulnerability of each potential recipient to climate change sourced from the University of Notre Dame Global Adaptation Initiative (ND-Gain, 2016) as well as several additional indicators of recipient need and donor self-interest. The data is discussed in more detail below.

4.1. Adaptation finance

An annual summary of the relevant adaptation finance data is shown below. As seen in Figure 1, the amount of allocated finance is increasing each year with most the increase in adaptation funding attributed to a rise in finance classed as 'significant' rather than that which has a 'principal' focus on adaptation.[15] This trend is expected to continue given the target to raise 100bn in climate finance by 2020. Whilst the total amount of funds classified as climate finance is increasing each year, closer inspection of the data (summarised visually for the year 2015 in

[13] In contrast to the first stage analysis carried out by Betzold and Weiler (2016), finance data from 2010 is not included in the analysis as upon closer inspection submissions from several key donors were absent suggesting they had not begun implementation of the adaptation marker.
[14] See Appendix 4 for a full list of donors and eligible recipients included in the analysis
[15] See Appendix 1 for a list of activities which qualify as "principal" under the climate change adaptation marker

Figures 2 and 3) suggests that the most vulnerable nations are not the ones receiving the most finance. Figures 2 and 3 clearly show a discrepancy between the level of need and the level of finance allocation. Japan and Germany are consistently the biggest donors over the 5 years (OECD, 2016).

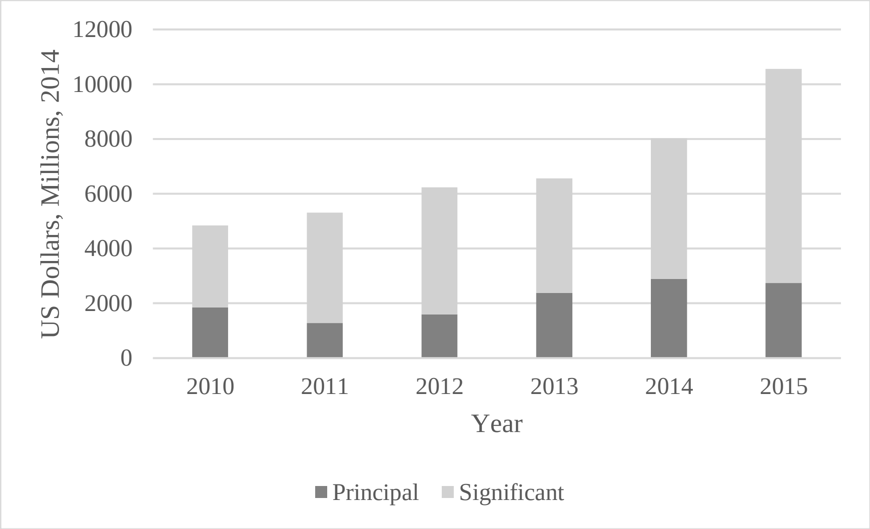

Figure 1: Adaptation finance (OECD, 2016)

4.2. Recipient need and finance performance variables

The ND-GAIN Index's vulnerability indicator used in this study considers a country's vulnerability as being a function of the three components of exposure, sensitivity, and adaptive capacity (Chen et al., 2015). [16] The vulnerability sub-index score is composed of 36 indicators (Chen et al., 2015). The ND-GAIN Index incorporates both a vulnerability and a readiness index which consist of components related to governance, social and economic readiness (see ND-GAIN, 2015 for more information). All components of the ND-GAIN Index follow a "proximity-to-goalpost" approach with the score values of all variables standardised to fall between 0 and 1. For each indicator that measures vulnerability, the indicator score shows a country's distance from a target of zero (the lowest possible score). As discussed in Section 3, to engender correct estimates a country's vulnerability to climate change must be metered against variables which describe that country's ability to cope with climate change impacts. Disaggregating the ND-GAIN index's readiness component provides governance, social and economic readiness indicators well suited to this purpose.

[16] The construction of the vulnerability index involves the specification of an emission scenario. The future climate predictions based on the chosen scenario inform the exposure component of the vulnerability indicator. Donor attitude towards climate change and varying levels of donor confidence in the construction methodology of climate scenarios in general 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.

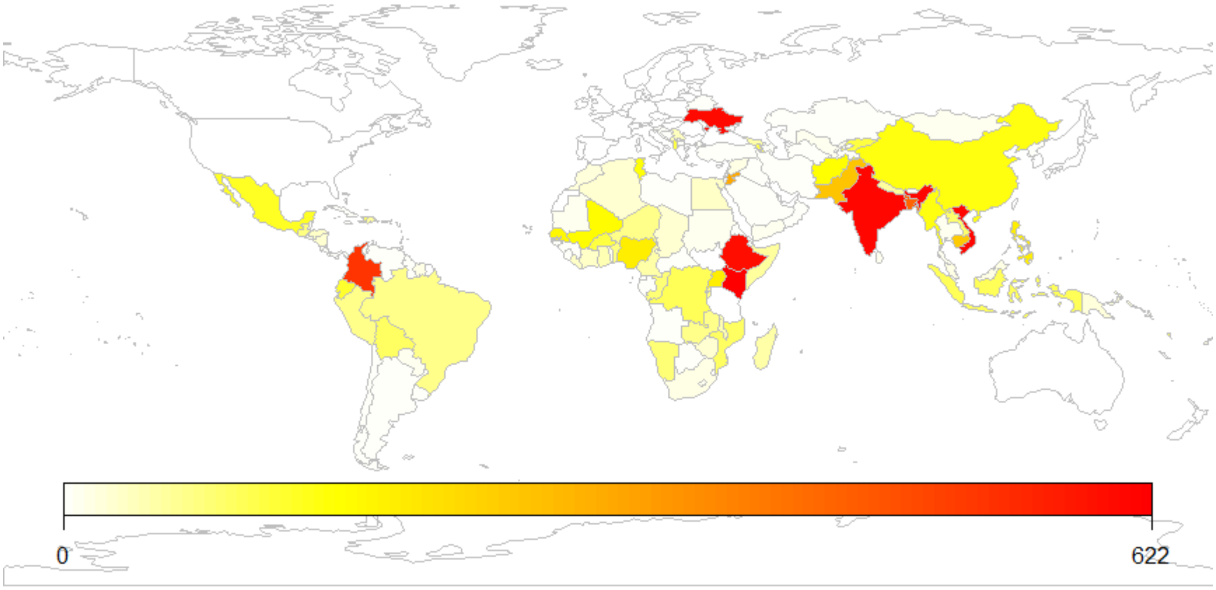

Figure 2: Donor Allocated finance in 2015 (USD 2014 million)

Author generated graphic, data source: OECD, 2016[17]

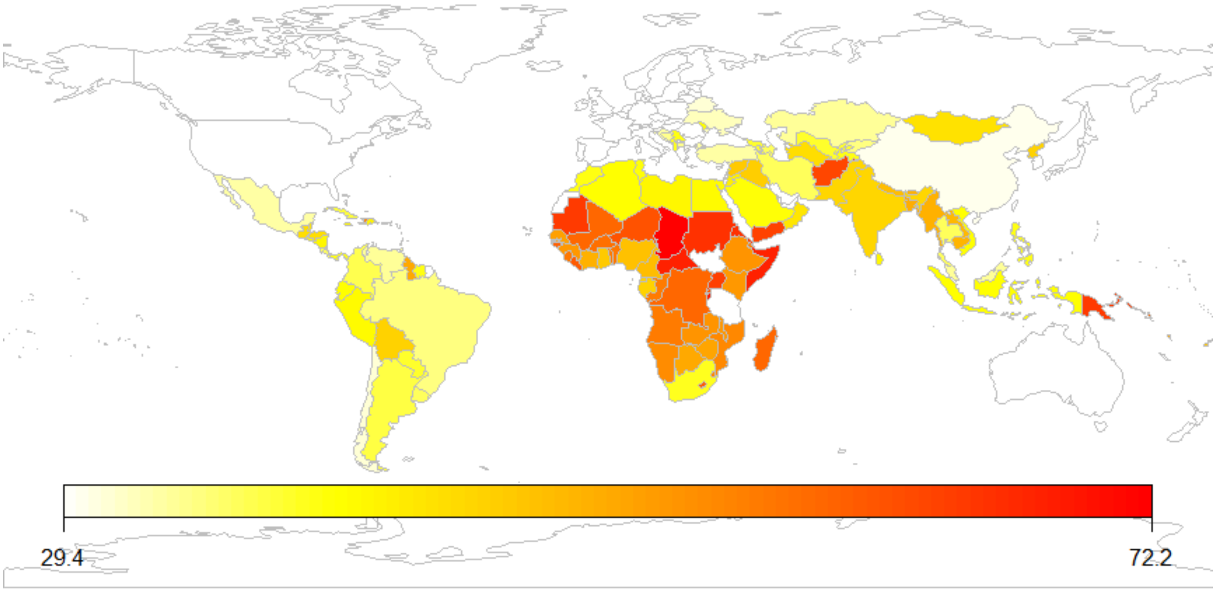

Figure 3:Recipient Climate Change Vulnerability in 2015
(standardized scale shifted to between 0-100, 100 being the most vulnerable)
Author generated graphic, data source: Notre Dame, 2016

[17] Total finance received by Ukraine capped at 622 million (max of next largest finance recipient; Kenya) to improve scale visibility. Ukraine received a combined total of adaptation finance (principal + significant) amounting to 1022 million (USD 2014) in 2015.

Governance readiness measures the stability of the society and institutional environment that contributes to investment risks, social readiness measures social conditions that help society to make efficient and equitable use of investment and economic readiness measures the investment climate that facilitates mobilizing capital from the private sector. A country's vulnerability is negatively correlated with all the readiness components (see Figure 2)[18].

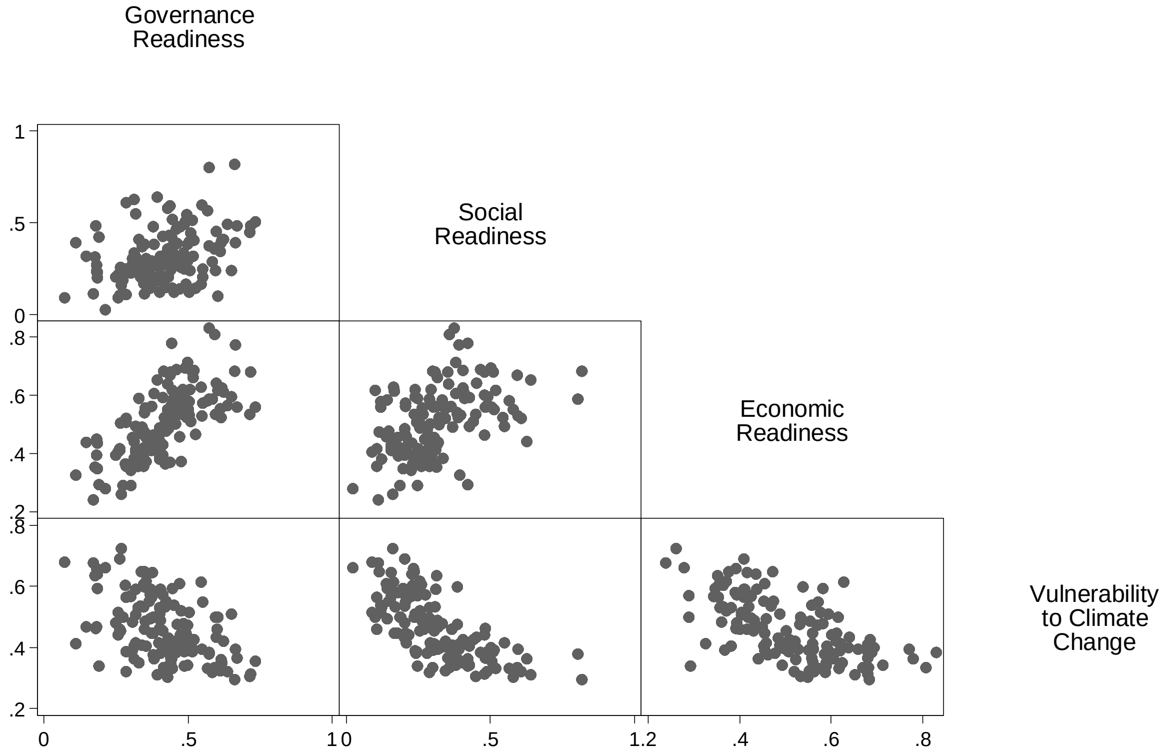

Figure 4:Dissaggregated ND-GAIN Index (ND-GAIN, 2016)

The ND -GAIN Index explicitly does not include Gross Domestic Product (GDP) per capita to avoid doubly penalizing developing countries whose low adaptive capacity and readiness is correlated with low GDP. Betzold and Weiler (2016) chose not to include the readiness components of the index in their analysis quoting fears of collinearity as include GDP per capita in their analysis. As checks for collinearity raised no immediate alarms[19], both GDP per capita and the readiness components will be included in the analysis both individually and simultaneously to examine the resulting sensitivity of the estimators. Appendix 6 shows the relationship between vulnerability and GDP for each global region included in the analysis; the graphic provides a visual representation of the range of levels of vulnerability and GDP per

[18] See Appendix 5 for a discussion about the relative spread of these indices
[19] All variance inflation factors (VIFs) <10

capita by region. GDP per capita data is sourced from The World Bank Databank (2016). Also sourced from the World Bank Databank (2016) is the total population of potential recipients which is included both as a measure of recipient need and as a way of avoiding large populous nation like India and China dominating the poverty (and potentially other) coefficients (Clist, 2009).

4.3. Donor self interest

Key variables related to donor self-interest included in this study are the distance between the donor and recipient; the level of bilateral trade between the country pairs and the recipient's level of political allegiance to the donor. The distance between donors, measured in kilometres, was sourced from Ceppi's GeoDist database (Mayer and Zignago, 2011). Trade data, for each year of the study, was sourced from the UNCTADstat database (UNCTAD, 2016). Total exports, measured in thousands of dollars (annual), were compiled into aggregated annual bilateral trade amounts. A voting similarity index calculated by Voeten (2013) which captures how often each country pair agrees according to UN voting records, is used as a proxy for political allegiance. The voting similarity index is a standardised variable with a range of 0-1. The colonial history of recipients, sourced from the ICOW Colonial History Data Set (Hensel, 2014), was used to generate a dummy signifying whether the donor was the potential recipient's main colonial power. This variable was included as 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).

To gain more insight into donor's strategic motivations not explicitly obvious in recipient specific or dyadic variables, network analysis techniques were employed to create two additional variables. The first being a hub score generated from an analysis of the global trade network for each year of the study and the second being the indegree centrality of each recipient node in the adaptation finance network.[20] The inclusion of each recipient node's indegree centrality in the analysis is a means of testing for donor coordination. Higher hub scores are an indication of the demand for the goods that each recipient exports.[21] Recipient hub scores contain a level of signalling related to the quality, type and importance of the goods that each potential finance recipient is exporting over and above that which can be inferred from aggregate trade figures.[22]The calculation of hub and authority scores is iterative; a node's hub

[20] This is simply a count of all incoming connections (positive finance allocations) in a given year
[21] Appendix 7 provides an overview of the global trade network and resulting hub scores for the year 2015.
[22] Pajek, a network analysis was used to compute the network scores for each recipient for each year of the study

score is boosted when it is connected to a node which has a high authority score, where a high authority score attributed to a node which is an important global importer[23]. A node's authority score is improved when it is connected to nodes which have high hub scores, where a high hub score is attributed to a node which is an important global exporter. Even when the total export amount for nodes are similar and small, different exporters will receive different hub scores dependent on their overall position and centrality in the network. Two countries which 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. The decision was made to prioritise hub scores over authority scores as adaptation finance is key to maintaining the productive capacity in developing nations providing a strong link to the export orientated hub 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).

4.4. Descriptive statistics

In Table 1 and Table 2 shown overleaf, descriptive statistics are provided for all variables used in the empirical analysis. Table 1, shows statistics for those observations where finance (principal and/or significant) wasn't provided. Table 2 considers a restricted sample consisting of only those observations which record a positive amount of finance. The complete dataset which forms the basis of the full model consists of 17747 individual observations including 4328 instances of positive funding.

Immediately obvious is that on average, those countries which receive finance tend to have a higher hub score, have a higher level of aggregate bilateral trade, tend to be more vulnerable to climate change (by approximately +4.5%) and have a lower GDP per Capita.

These findings suggest that both donor self-interest and recipient need are key determinants of the donor decision making process. All the readiness indicators are smaller when only those donor/recipient pairs where money was transferred are considered supporting the assertion that donors consider recipient need. Counter intuitively, members of the association of small island states (AOSIS) countries are less well represented in the finance received sub sample.

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

Table 1: Descriptive Statistics: Restricted Sample (No Finance Received)

Variables	Mean	SD	Min	Max
Principal finance (US $, Millions, 2014)	0	0	0	0
Significant finance (US $, Millions, 2014)	0	0	0	0
Vulnerability	0.45	0.10	0.29	0.73
Bilateral Trade (exports in $'000, annual)	723585	8264999	0	5.27E+08
Population	3.36E+07	1.39E+08	52998	1.37E+09
AOSIS	0.23	0.42	0	1
Agree in UN	0.75	0.15	0	1
Distance (km)	7647.25	3931.16	117.35	19629.50
Colonial History	0.02	0.13	0	1
GDP per Capita (2011 international $)	10659.56	9921.04	565.60	49618.85
Governance readiness	0.43	0.13	0.12	0.75
Social readiness	0.32	0.16	0.02	0.87
Economic readiness	0.49	0.13	0.20	0.83
Hub score	0.01	0.99	-0.21	11.69
In degree centrality	5.40	4.34	0	23

Table 2: Descriptive Statistics: Restricted Sample (Finance Received)

Variables	Mean	SD	Min	Max
Principal finance (US $, Millions, 2014)	2.51	15.97	0	483.74
Significant finance (US $, Millions, 2014)	5.61	29.14	0	999.47
Vulnerability	0.47	0.10	0.30	0.73
Bilateral Trade (exports $'000, annual)	4014024	25900000	0	5.59E+08
Population	8.07E+07	2.34E+08	52998.00	1.37E+09
AOSIS	0.09	0.29	0	1
Agree in UN	0.71	0.17	0.0625	1
Distance (km)	7904.60	3569.86	394.75	18600.70
Colonial History	0.06	0.24	0	1
GDP per Capita (2011 international $)	6554.63	5547.77	565.60	47829.66
Governance readiness	0.39	0.10	0.12	0.75
Social readiness	0.27	0.11	0.02	0.79
Economic readiness	0.47	0.11	0.20	0.83
Hub score	0.15	1.41	-0.21	11.69
In degree centrality	9.15	4.75	0	22

By splitting lagged vulnerability variable into 4 quartiles, it is possible to see how the value of key variables changes over the range of the variable. Table 3 shows descriptive statistics for the whole sample split by quartile of vulnerability (lagged). A consistent trend is observed in the size of both principal and significant finance packets allocated to recipients. On average, the size of the packets of finance allocated increases in line with vulnerability up to a point, and then rapidly declines. Principal finance exhibits a turning point in the 2nd quartile of vulnerability (lagged) whereas significant finance peaks in the third quartile. This is clear evidence of a non-linear relationship between vulnerability and finance allocation. Both hub scores and GDP per capita consistently decrease from the 1st to the 4th quartile.

Table 3: Selected Statistics by Quartile of Vulnerability (lagged)

	Mean	SD	Min	Max
1st Quartile of Vulnerability to Climate Change (Lagged)				
Lagged Vulnerability	0.347	0.025	0.293	0.389
Principal finance (US $, Millions, 2014)	0.371	7.890	0	361.030
Significant finance (US $, Millions, 2014)	0.711	15.664	0	999.469
Lagged Hub Score	0.037	0.116	2.08E-06	0.683
GDP per Capita (2011 international $)	15640.440	6774.957	2122.990	31925.970
2nd Quartile of Vulnerability to Climate Change (Lagged)				
Lagged Vulnerability	0.411	0.016	0.389	0.446
Principal finance (US $, Millions, 2014)	0.848	10.439	0	483.741
Significant finance (US $, Millions, 2014)	1.220	12.683	0	426.929
Lagged Hub Score	0.009	0.018	1.44E-06	0.108
GDP per Capita (2011 international $)	13501.670	10321.180	2229.446	49618.850
3rd Quartile of Vulnerability to Climate Change (Lagged)				
Lagged Vulnerability	0.494	0.028	0.447	0.543
Principal finance (US $, Millions, 2014)	0.706	7.147	0	278.732
Significant finance (US $, Millions, 2014)	2.050	18.159	0	698.582
Lagged Hub Score	0.005	0.013	0.00E+00	0.070
GDP per Capita (2011 international $)	6453.146	7867.036	1066.042	47829.660
4th Quartile of Vulnerability to Climate Change (Lagged)				
Lagged Vulnerability	0.606	0.044	0.543	0.726
Principal finance (US $, Millions, 2014)	0.334	2.806	0	81.402
Significant finance (US $, Millions, 2014)	1.121	5.617	0	113.423
Lagged Hub Score	0.001	0.004	1.76E-06	0.028
GDP per Capita (2011 international $)	2494.452	2031.429	565.595	9502.979

5. Empirical Strategy

A key issue with dealing with aid data is that many countries receive no assistance meaning a significant number of observations are clustered at zero. If OLS was used on the whole sample, model estimates would therefore be biased toward zero (Clist, 2011). There are three main approaches that have been applied in the literature in the context of aid allocation to overcome this issue; a two-part model, a Tobit (type 1) model and a Heckman Selection model. To determine the best estimator in this context, a review of the different approaches, their assumptions and the analysis of relevant specification tests is required.[24]

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

[24] For a more in depth discussion of the various estimators see Clist, (2009), Neumayer (2003) and Cameron and Trivedi (2005).

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, whilst I propose that the selection and allocation stages be estimated using an identical set of variables (there appears to be no good reason not to do so), 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 which 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 upon the selection decision differently for different donors. Neumayer himself 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 is 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 $Cov[\varepsilon_1, \varepsilon_2] = 0$. In contrast, the Heckman selection model explicitly allows the error terms from both stages of aid allocation to be correlated. Whilst theoretically the validity of the two-part model relies on the assumption that the 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 being 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 whilst 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. [25] To test which model is more suited to my dataset, I first derive the econometric model for each stage of the two-step hurdle model and then formally test whether the two -part model or the Heckman Selection model is more appropriate.

5.1. Econometric specification

As presented in section 3.2, climate finance allocation is conceptualised as a two-step process. In the first stage, donors select which countries they are going to allocate finance to. 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 allocated budget share is represented by the variable

[25] Belsely et al. (1980) suggest a VIF of 10-100 would indicate issues, with a VIF>30 considered severe

a_r . The relationship between a_r^*. and its determinants shown in equation 22 is approximated by the econometric specification presented below in equation 23. Equation 23 describes the second stage of the hurdle model:[26]

$$\begin{aligned}\ln\left(a_{r,t}^{*}\right) = \beta_0 + \beta_1\left(v_{r,t-1}\right) + \beta_2\left(v_{r,t-1}\right)^2 + \beta_3 \ln\left(n_{r,t-1}\right) + \beta_4\left(x_{r,t}\right) + \beta_5 \ln\left(y_{r,t-1}\right) \\ + \beta_6\left(g_{r,t-1}\right) + \beta_7 \ln\left(t_{r,t-1}\right) + \beta_8\left(hub_{r,t-1}\right) + \beta_9\left(p_{dr,t-1}\right) + \beta_{r,t} \\ + \delta_{d,t}^{st.2} + \eta_t^{st.2} + \varepsilon_{d,t}^{st.2} \quad \ldots \text{ (eq. 23)}\end{aligned}$$

Where v_r represents a recipient's vulnerability to climate change; n_r is the recipient's population; x_r is a recipient's indegree centrality in the adaptation finance network; y_r is the recipient's GDP per capita; g_r is the recipient's level of governance readiness; t_r is the aggregate amount of bilateral trade between the donor and recipient; hub_r is the recipient's importance in the global trade network (represented by their 'hub score'); and p_{dr} is the level of political allegiance between the donor and recipient. 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.

I add a vulnerability squared term to the specification to allow the marginal effect of vulnerability on $\ln\left(a_r\right)$ to change over the range of the variable. This addition allows the concave relationship between vulnerability and a_r observed in Table 3 to be modelled.

The dependent variable, $\ln\left(a_{r,t}^{*}\right)$, represents the log transformed share of allocated adaptation finance. I plus one to all aggregate bilateral trade amounts before log transforming them to avoid dropping the zero values. Dropping zero values is not a concern when log transforming the dependent variable, as the second stage only considers positive amounts of allocated finance.

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. 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). β_r represents a vector of

[26] If the relationship between P_r, I_r, S_{dr} in equation 22 was multiplicative logging equation 22 would result in a log-log model with a similar specification to that shown. As the introduction of EUT into the model makes the relationship between the variables additive, equation 23 approximates the log of equation 22

weights (w_r) attached to each recipient by donors in stage two. Included therein are the social and economic readiness components from the ND-Gain Index. These values indicate the ability of recipients to respond to climate impacts on their own (ND-GAIN, 2016). Each readiness index, the governance readiness index included, enters the model in their standardised form with a range between 0-1. Additional weights include a control variable signalling whether a recipient is a member of the association of small island states (AOSIS) and a variable indicating whether the donor was the potential recipient's main colonial power.

As I acknowledge that donors might have different subjective measures of the impact of adaptation finance to a recipient, I therefore introduce fixed donor effects, δ_d, into the model specification to control for donor differences. The fixed effect approach was chosen over a random effects model as the assumption that the unobserved variables are assumed to be statistically independent of all the observed variables did not appear reasonable in this context[27]. A Hausman test supported this decision.

Finally, to control for the possibility of simultaneity and to allow for information lags it is assumed that donors only have access to recipient specific data in the period following the finance allocation decision. To reflect this, all recipient specific independent variables are lagged by one year (Balla and Reinhardt, 2008). [28] To control for heteroscedasticity, robust standard errors are used. Standard errors are clustered at the donor level when donor (cluster-specific) fixed effects are introduced. As discussed by Cameron and Miller (2015), failure to control for within-cluster error correlation can lead to misleadingly small standard errors, and consequently misleadingly narrow confidence intervals, large t-statistics and low p-values.

In the first stage of the model, the dependent variable is a binary selection variable and is therefore modelled using a Probit regression.[29] The first stage model variables are identical to those included in the second stage as shown below:

$$\begin{aligned}\Pr(F_{drt}=1) = {} & \alpha_0 + \alpha_1(v_{r,t-1}) + \alpha_2(v_{r,t-1})^2 + +\alpha_3 \ln(n_{r,t-1}) + \alpha_4(x_{r,t}) + \alpha_5 \ln(y_{r,t-1}) \\ & + \alpha_6(g_{r,t-1}) + \alpha_7 \ln(t_{r,t-1}) + \alpha_8(hub_{r,t-1}) + \alpha_9\,(p_{dr,t-1}) + \alpha_{r,t} \\ & + \delta_{d,t}^{st.1} + \eta_t^{st.1} + \varepsilon_{dr,t}^{st.1} \;\ldots\; (\text{eq. } 24)\end{aligned}$$

[27] See section 5.3 for a discussion on the validity of using fixed effects in the first stage

[28] The few exceptions being x_r, which represents the indegree centrality of the recipient nodes in the current year's adaptation finance network, and the static control dummies.

[29] Equation 24 approximates the probability model that would result from subbing equation 1 into equation 2 and using logarithms. Accounting for the fact that there are multiple donors and introducing time and donor fixed effects would equate the two derivations in regard to the independent variables included therein.

Where $\Pr(F_{drt} = 1)$ represents the probability of selection and $\alpha_{r,t}$ represents the weights (w_r) attached to each recipient by donors in stage 1. Whilst 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, it is predicted that

$$\beta_1\&\alpha_1 < 0;\ \beta_2\&\alpha_2 > 0;\ \beta_3\&\alpha_3 > 0;\ \beta_4\&\alpha_4 > 0;\ \ \beta_5\&\alpha_5 < 0;\ \ \beta_6\&\alpha_6 > 0;\ \beta_7\ \&\alpha_7; > 0;\ \beta_8\&\alpha_8 > 0$$

$$\text{and}\ \ \beta_9\&\alpha_9 > 0$$

A key assumption with the hurdle model specified is that $Cov\left[\varepsilon_{d,t}^{st.1}, \varepsilon_{d,t}^{st.2}\right] = 0$, whether this holds in the context of the specified model will be formally tested in the next section.

5.2. Specification tests

I carry out two tests in order to evaluate the overall specification of the model. Firstly, to test the level of covariance between the stage one and stage two error terms I estimate a Heckman selection model using the specification outlined in equation 23. As outlined by Clist (2009), no exclusion restriction is specified. As the covariance, Rho, is equal to 0.42 and the Prob > chi2 = 0.0012, independence is rejected meaning a key assumption of the two-part model is violated.

To test the validity of using the Heckman Selection model without an appropriate exclusion restriction, the first stage Probit is run and then the IMV calculated. The IMV is then included in the second stage regression and the corresponding VIF inspected. Given that the VIF of the IMV is =26.2, which is close to the threshold collinearity level (VIF=30) tentatively proposed by Madden (2008)[30], and that there is evidence that the bias associated with $Cov[\varepsilon_1, \varepsilon_2] \neq 0$ is small (Neumayer, 2003 and Manning et al., 1987) the two-part model (Probit/OLS) is deemed the appropriate estimator.

Variance inflation factors were analysed after running both stages; all calculated VIFs were less than 10 indicating no concerns related to multicollinearity from an econometric perspective.[31]

5.3. 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,

[30] Belsely et al. (1980) suggest a VIF of 10-100 would indicate issues, with a VIF>30 considered severe

[31] A LPM model was specified for the first stage to allow computation of the VIFs

Z, increases so too do the number of incidental parameters resulting in the incidental parameters being inconsistently estimated as Z $\rightarrow\infty$. The problem being 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)[32].

Following Beck (2015) if the total number of parameters is G + k, and the number of observations is NG (where N = group size, G= number of groups and k = the number of covariates) whilst it is not advisable to estimate a model where the number of parameters $\approx$ the number of observations (as described by the Incidental parameter problem), that issue is orthogonal to the issue that G of the parameters are group specific intercepts.

Beck (2015) uses Monte Carlo simulations to show that if N is large enough, the results from a logit model using fixed effects dummies exhibit very little bias[33]. As the fixed effects included in equation 23 are not specified at the individual level, the groups are well balanced and that the smallest group's size in the first stage is >100, specifying fixed effects dummies is not an issue in terms of bias. [34] As an aside, using xtlogit with the fixed effects set at the donor/recipient level results in >13000 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 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). In the case of the current research, this is not an issue as the groups are balanced and large (>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[35].

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[32] See Cameron and Trivedi (2005, p. 726) for a more in-depth discussion

[33] 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.

[34] i.e. α doesn't increase with N

[35] i.e. in the case of the first stage as G is large relative to k, c$\approx$1 for within estimation and c $\approx$ N/(N-1) $\approx$ 1 for (LS)DV estimation, see Cameron and Miller (2015) p.331 for more information.

6. Results

6.1. Stage 1: recipient selection

The stage 1 analysis uses a Probit regression to estimate the average donor selection behaviour over the 5-year period between 2011 and 2015. Table 4 includes results for five nested models which consider the determinants of selection as an adaptation finance recipient based on the full sample[36]. Table 4 is organised as follows; specification 1 includes no fixed effects, year fixed effects are introduced in Specification 2. Donor and year fixed effects are included in specification 3. The main model, specification 4, reflects equation 24. Specification 4 includes the social and economic readiness variables in addition to donor and year fixed effects. Specification 5 adds the indegree centrality of recipient nodes in the adaptation finance network. Robust standard errors are used in specification 1 and 2 with standard errors clustered at the donor level in models 4 and 5. Both robust and cluster robust standard errors are reported for specification 3 for comparison.

Tests for multicollinearity show that the inclusion of the indegree centrality variable in the analysis is not problematic econometrically, however, its inclusion complicates the interpretation of the results. It is reasonable to assume a suppressor effect would be occurring as all donors have access to the same set of information. For this reason, specification 5 is considered separately to specification 1 through 4. Nonetheless, indegree centrality (a count of the number of donors who selected a recipient in a given year, not including the selection decision in question) is highly significant and positive upon inclusion in specification 5. This is strong support against donor coordination indicating that donors are more likely to select recipients whom have been selected by other donors as hypothesised in H2.5. This finding contrasts that of Betzold and Weiler (2016) who found evidence for donor coordination when considering the determinants of selection for adaption finance using temporal exponential random graph models. The other network variable, hub scores, is considered a key indicator of donor strategic interests. The coefficient for hub scores is negative and significant in specification 1 through 4, providing evidence that donors are less likely to select important global exporters as finance recipients as hypothesised in H2.4.

Model 1 doesn't include any readiness variables; these variables are added in specification 4 to test the sensitivity of the specification to their inclusion. Higher social readiness, an indicator of social conditions that help society to make efficient and equitable use of investment (ND-GAIN, 2016), is associated with a lower probability of selection. This result is highly significant

[36] The full sample considers all allocated finance = principal + 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 social actors to work together, this result supports the assertion that recipient need is a key indicator of selection. Conversely, the coefficient for economic readiness (which measures the ease of doing business), is positive and significant, indicating a good business environment encourages selection. The coefficient for governance readiness, expected to increase the likelihood of selection, is positive and significant at the 1% level in the full model (Model 4) providing evidence for H1.3. There was initially concern about including the readiness variables and GDP per capita in the model, as both the readiness indicators and GDP per capita function as signals of the recipient's capacity to cope with the negative impacts of climate change. Whilst the inclusion of the readiness indices does influence the magnitude of the coefficient of (ln) GDP per capita, overall this concern appears unwarranted as ln (GDP per capita) remains statistically significant at the 1% level and maintains its negative relationship to the dependent selection variable upon their inclusion in model 4. The economic and social readiness variables essentially cancel each other out. In support for the hypothesis H1.1, higher levels of GDP are shown to reduce the likelihood of selection across all models.

As hypothesised, the colonial history variable is positive and significant at the 1% level in all models, a finding which is robust when clustered standards errors are specified in model 3 and 4. This supports H2.2, indicating that donors are more likely to select their former colonies as adaptation finance recipients.

The coefficient of ln(distance), though initially positive and significant, becomes negative and significant once donor fixed effects are added. The negative sign implies that donors are less likely to select recipients that are further away; distance from the donor is considered a proxy for strategic interests. In support of H1.4, the coefficient of (ln) population is positive and significant at the 1% level in models 1 through 4 suggesting donors prioritise more populous nations.

In contrast to expectations, the coefficient for AOSIS is not significant in model 4 suggesting small island states are not significantly more likely to be selected as finance recipients. In model 3, the coefficient of AOSIS is positive and significant at the 10% level, even when clustered standard errors are used. It is the introduction of the additional readiness indices that causes the shift in significance.

Table 4: Stage 1 coefficients from Probit Regression

Variables	(1)	(2)	(3)	(4)	(5)
	Probit Regression. Dependent Variable: Binary Selection				
Vulnerability lagged	10.02*** (1.250)	10.03*** (1.250)	15.80 (1.385) *** [2.415] ***	12.11*** [2.290]	4.407* [2.258]
Vulnerability lagged squared	-10.54*** (1.257)	-10.54*** (1.257)	-16.57 (1.367) *** [2.350]***	-13.24*** [2.210]	-4.882** [2.189]
ln(Bilateral Trade lagged)	0.209*** (0.00776)	0.209*** (0.00776)	0.0799 (0.0103) *** [0.0161] ***	0.0774*** [0.0159]	0.0869*** [0.0176]
ln(Population lagged)	0.0616*** (0.0114)	0.0620*** (0.0114)	0.255 (0.0154) *** [0.0286]***	0.238*** [0.0292]	0.0303 [0.0299]
AOSIS	0.0923** (0.0403)	0.0922** (0.0403)	0.182 (0.0442) *** [0.106]*	0.0742 [0.116]	0.0319 [0.120]
Agree in UN	0.138* (0.0802)	0.132 (0.0815)	-0.239 (0.163) [0.395]	-0.271 [0.384]	-0.200 [0.400]
ln(distance)	0.230*** (0.0211)	0.229*** (0.0211)	-0.167 (0.0268) *** [0.0953] *	-0.213** [0.101]	-0.320*** [0.0982]
Colonial History	0.520*** (0.0634)	0.520*** (0.0634)	1.031 (0.0741) *** [0.349] ***	1.011*** [0.350]	1.052*** [0.338]
ln(GDP per capita lagged)	-0.524*** (0.0232)	-0.523*** (0.0233)	-0.470 (0.0248) *** [0.0346] ***	-0.455*** [0.0375]	-0.242*** [0.0457]
Governance readiness lagged	0.672*** (0.129)	0.678*** (0.129)	1.592 (0.146) *** [0.255] ***	0.963*** [0.331]	-0.0284 [0.334]
Hub score lagged (std.)	-0.0516*** (0.0107)	-0.0518*** (0.0107)	-0.0393 (0.0116) *** [0.0179] **	-0.0332* [0.0182]	-0.000554 [0.0194]
Social readiness lagged				-1.038*** [0.271]	-0.792*** [0.263]
Economic readiness lagged				0.974*** [0.290]	0.651** [0.313]
In degree centrality					0.110*** [0.00728]
Year fixed effects	No	Yes	Yes	Yes	Yes
Donor fixed effects	No	No	Yes	Yes	Yes
Observations	18,139	18,139	18,139	17,747	17,747
Pseudo R2	0.203	0.203	0.332	0.338	0.371
% Correctly Predicted	79.78	79.86	83.47	83.45	84.81

Note: the first part of the model 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

The negative coefficient associated with the political alliance proxy (Agree in UN) in specification 4, although not significant, 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 they are less politically aligned. This is contrary to the expectation that donors would prioritise political allies as outlined in H2.1.

The key variables of interest are arguably (lagged) vulnerability and (lagged) vulnerability squared. Both variables are significant across all specifications, even when standard errors are clustered at the donor level. Whilst the magnitude is of interest, a key issue is the difference between the two terms as this defines the degree of concavity of the resulting relationship between vulnerability and selection. Whilst it is difficult to ascertain the exact affect that an increase in (lagged) vulnerability has on the probability of selection by considering the output from the Probit regressions included in table 4, it is evident that the negative sign associated with the squared term indicates a concave function. This suggests limited support for hypothesis H1.2. The interaction between the two variables will be explored more when marginal effects are considered in section 6.1.1.

6.1.1. Comparing marginal effects: total vs. principal vs. significant

Calculating the marginal effects associated with the coefficients of the first stage improves the interpretation of the impact that the independent variables have on the probability of selection. The marginal effects reported in table 5 measure the expected change in the probability of being selected, due to a unit change in the relevant independent variable. Table 5 reports the average marginal effects associated with the full model (model 4). The marginal effects in column M1 were computed using the full sample, column M2 restricts the sample to finance classified as principal whilst M3 considers only finance classified as significant.

Due to the inclusion of vulnerability as an interaction term to allow for the correct calculation of the marginal effects, the marginal effect of vulnerability and vulnerability squared is combined into one (linear) coefficient in table 5. The marginal effect of (lagged) vulnerability on selection for model 4, calculated at 0.05 unit intervals across the range of the variable, is shown in Figure 5. I find that the result is clearly concave with the probability of selection increasing until the vulnerability lagged 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. This result shows that whilst an increase in vulnerability improves the probability of selection up to a point, ultimately the most vulnerable tend to be selected less as finance recipients. The marginal effect is statistically significant at the 1% level across the entire range of the variable, independent of whether the whole sample or a restricted subset is used (see Appendix 8).

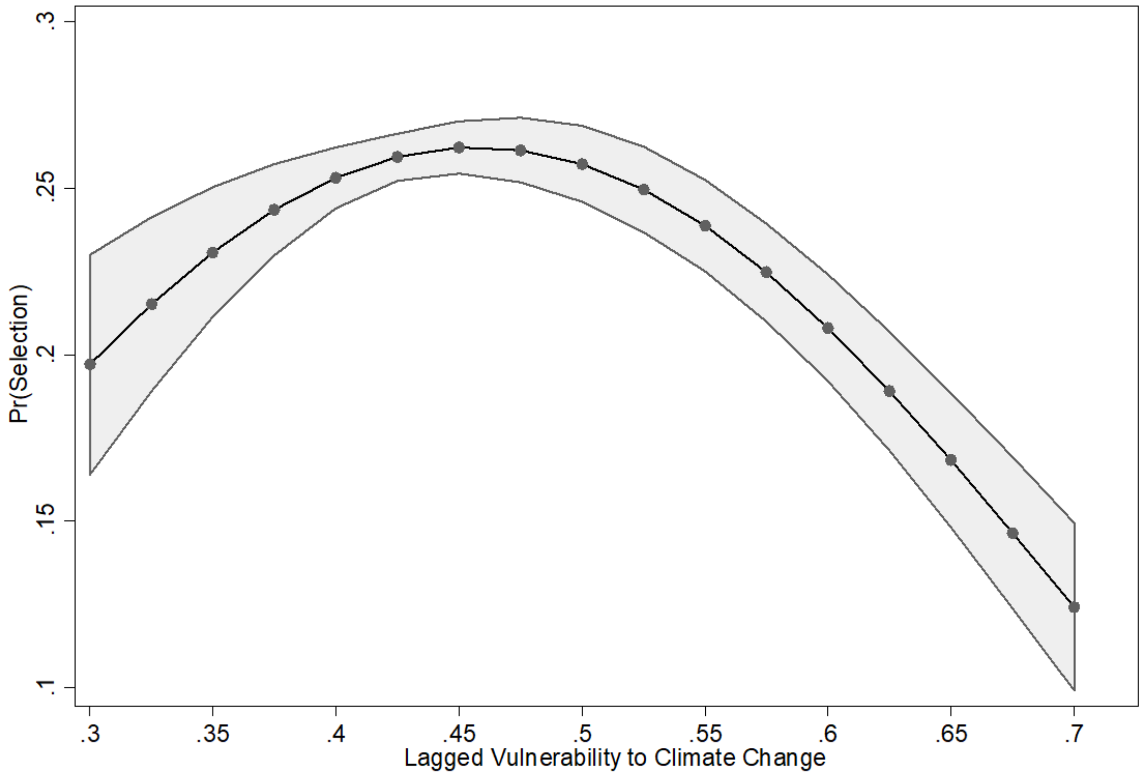

Figure 5: Marginal effect of vulnerability on probability of selection with 95% confidence Interval

Comparing the different samples provides further insight into donor behaviour. A notable difference between the three different outputs is that the small island states dummy variable (AOSIS) is significant only when the sample is restricted to finance classed as principal (M2). In M2, a discrete change in AOSIS increases the average likelihood of selection by 5.3% significant at the 5% level. This result suggests that donors regard recipient need more highly when principal classed projects are concerned, even if the overall probability of selection for such finance is lower. This finding raises questions around how an increase in the amount of funding provided by donors would impact on a more vulnerable country's probability of being selected as a finance recipient. As discussed, significant classed adaptation finance makes up the bulk of allocated finance, and is expected to continue to do so as the overall amount of climate finance increases to meet the 100bn target set for 2020. The lower number of observations shown in M2 is a result of two countries, the Slovak republic and Slovenia, not giving any principal classed finance. As a result of no variation being found in these observations, all observations associated with these countries were dropped.

Table 5: Average Marginal Effects

Average Marginal Effect (dydx) based on specification 4 in table 4			
	(M1) **Principal and Significant**	**(M2)** **Principal**	**(M3)** **Significant**
Variables	**Dependent Variable: Binary Selection**		
Vulnerability lagged	-0.0711	-0.0308	-0.0262
	(-1.01)	(-0.46)	(-0.38)
ln(Bilateral Trade Lagged)	0.0156***	0.00907***	0.0151***
	(4.85)	(3.00)	(4.70)
ln(Population lagged)	0.0479***	0.0335***	0.0409***
	(8.65)	(6.18)	(8.18)
AOSIS	0.0149	0.0529**	-0.0136
	(0.64)	(2.18)	(-0.70)
Agree in UN	-0.0544	-0.0289	-0.0275
	(-0.70)	(-0.43)	(-0.38)
ln(distance)	-0.0428**	-0.0220	-0.0423**
	(-2.10)	(-1.40)	(-2.31)
Colonial History	0.203***	0.139***	0.186***
	(2.96)	(2.99)	(2.69)
ln(GDP per capita lagged)	-0.0916***	-0.0568***	-0.0811***
	(-12.75)	(-8.11)	(-11.64)
Governance readiness lagged	0.194***	0.149***	0.191***
	(2.96)	(4.17)	(3.15)
Social readiness lagged	-0.209***	-0.0960***	-0.227***
	(-3.83)	(-2.70)	(-5.27)
Economic readiness lagged	0.196***	0.151***	0.182***
	(3.31)	(2.93)	(3.32)
Hub score lagged (std.)	-0.00668*	-0.00411	-0.00422
	(-1.84)	(-1.60)	(-1.36)
N	17747	16484	17747

t statistics in parentheses, standard errors clustered at the donor level,
time and donor fixed effects included in model estimation
* $p < .10$, ** $p < .05$, *** $p < .01$

If donors are indeed less stringent about which nations they select as recipients of finance classed as significant, an increase in adaptation finance is not guaranteed to coincide with a comparable increase in the probability of the most vulnerable countries being selected as finance recipients.

The magnitude of the effect of (ln) bilateral trade remains significant at the 1% level and relatively unchanged for all types of finance. Whilst this finding is in line with the direction of the relationship outlined in H2.3, the magnitude of the effect is much smaller than expected; in M1 a 10% increase in ln (bilateral trade lagged) increases the probability of selection by 0.15% on average, an arguably small amount[37]. A 10% increase in ln(distance) decreases the probability of selection for total finance by a similarly small amount of 0.4%. Both these results are small in comparison to the impact that a discrete change in the colonial history variable has

[37] 0.0156*ln(1.1) =0.0015=0.15%

on the probability of selection; in M1 former colonies are approximately 20% more likely to be chosen as finance recipients on average providing strong support for H2.2.

6.2. Stage 2: finance allocation

The stage two analysis considers the extensive margin decision, the results of which are presented in table 6. The arrangement of table 6 is the same as that used in stage 1; 5 nested specifications are presented. Time fixed effects are introduced in specification 7 and donor fixed effects are included in specification 8 through 10. Model 9 represents the specification outlined in equation 23. As before, the final specification in the table, specification 10 in this case, should be considered separately as it includes the indegree centrality variable which complicates the interpretation of coefficients.

As in the first stage, the coefficient of the vulnerability lagged squared term is once again negative and significant in all models indicating that not only are the most vulnerable countries less likely to be selected as finance recipients as shown in the stage 1 results, but they are also receive less finance than their less vulnerable neighbours. This result provides support for H1.2 up to a point; specifically, to the point where (lagged) vulnerability ≈ 0.525. Taking a closer look at the results for specification 9, it can be seen that on average, of those selected to receive finance, the least vulnerable receive a share which is very similar to the most vulnerable; about 0.16 percent of the donor's adaptation finance budget for that year.[38] Nations with a (lagged) vulnerability rating of approximately 0.525 receive on average the largest finance endowment ≈ 0.37% of a donor's budget. [39] What is immediately striking is how small these percentages are; the vast majority of adaptation finance allocations represent less than 1% of the respective donor's annual adaptation budget with the mean budget share of finance allocated being 0.63%. This high level of dispersion is in accordance with the developed theory (see Proposition 1). The other key indicator for recipient need, GDP per capita is also significant at the 1% level, across all models with the result robust to the inclusion of donor fixed effects and the clustering of standard errors. This is clear evidence that donors consider recipient need when allocating funding in line with H1.1. The coefficient of (lagged) hub scores, a network variable included as a proxy for donors' strategic interests, is positive but not significant in all specifications. As in stage one, the social readiness coefficient is consistently negative whereas the economic readiness coefficient is positive. The social and economic readiness variables are significant at the 10% and 5% level respectively in specification 9.

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[38] exp(-1.8) ≈0.16%

[39] exp(-1) ≈0.37%

Table 6: Stage 2 results

Variables	(6)	(7)	(8)	(9)	(10)
	Dependent Variable: ln (share of total adaptation finance)				
Vulnerability lagged	34.85*** (4.263)	35.31*** (4.266)	32.07 (3.993)*** [4.405]***	28.08*** [5.610]	17.08*** [5.679]
Vulnerability lagged squared	-35.06*** (4.046)	-35.44*** (4.048)	-30.64 (3.783)*** [4.238]***	-27.00*** [5.288]	-15.35*** [5.394]
ln(Bilateral Trade Lagged)	-0.148*** (0.0178)	-0.147*** (0.0178)	0.0692 (0.0232)*** [0.0353]*	0.0700** [0.0327]	0.0784** [0.0346]
ln(Population lagged)	0.498*** (0.0348)	0.502*** (0.0348)	0.297 (0.0389)*** [0.0928]***	0.277*** [0.0913]	0.0349 [0.109]
AOSIS	0.0992 (0.144)	0.0954 (0.143)	0.0477 (0.135) [0.263]	-0.130 [0.299]	-0.141 [0.298]
Agree in UN	-0.412** (0.209)	-0.374* (0.212)	0.0963 (0.457) [0.567]	0.0590 [0.614]	0.299 [0.601]
ln(distance)	-1.232*** (0.0697)	-1.237*** (0.0697)	-0.724 (0.0729)*** [0.180]***	-0.752*** [0.174]	-0.882*** [0.155]
Colonial History	0.973*** (0.170)	0.978*** (0.170)	1.553 (0.198)*** [0.621]**	1.538** [0.609]	1.620*** [0.568]
ln(GDP per capita lagged)	-0.484*** (0.0750)	-0.478*** (0.0751)	-0.495 (0.0706)*** [0.100]***	-0.487*** [0.111]	-0.239** [0.0985]
Governance readiness lagged	3.147*** (0.432)	3.209*** (0.431)	2.077 (0.420)*** [0.783]**	1.090 [0.644]	0.190 [0.631]
Hub score lagged (std.)	0.0204 (0.0317)	0.0191 (0.0315)	0.0141 (0.0322) [0.0498]	0.0250 [0.0519]	0.0597 [0.0546]
Social readiness lagged				-1.340* [0.673]	-0.899 [0.742]
Economic readiness lagged				1.363** [0.512]	0.798 [0.557]
Indegree centrality					0.127*** [0.0241]
Year fixed effects	No	Yes	Yes	Yes	Yes
Donor fixed effects	No	No	Yes	Yes	Yes
Observations	4,184	4,184	4,184	4,119	4,119
R2	0.171	0.174	0.293	0.294	0.317

Note: the second part 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

When interpreting the readiness variables, the fact that they fall within the range of 0-1 needs to be considered. As an example, in model 9, a 10% increase in social readiness would on average decrease the mean budget share of finance allocated to recipients in stage two by

12.54%[40]. This result, once again provides evidence that donors target those countries least ready to cope with the impacts of climate change. As predicted in H1.3, the sign of the coefficient of the governance readiness variable is once again positive and significant across specifications 6 through 8 but loses its significance once the additional readiness variables are added in specification 9. The positive and significant coefficient associated with indegree centrality shown in specification 10 confirms the results from stage one and provides further evidence against donor coordination in support of H2.5. Interestingly, whilst the coefficient of Agree in UN is negative and significant in models 6 and 7, in line with the findings of Hicks et al. (2010), once donor fixed effects are added the sign reverses and the significance disappears.

As expected from a strategic perspective, colonial history is a key determinant of allocation, with donors allotting on average a budget share approximately 5 times as large to former colonies. A 10% increase in (ln) distance reduces the budget share allocated by approximately 7%.[41] These results mirror those found in stage 1 and support H2.2; on average donors are both more likely to select ex colonies as recipients, and to allocate them more adaptation finance. Of final note, whilst the effect of an increase in (ln) bilateral trade is significant in all models, it is only when donor fixed effects are introduced that the relationship is positive as hypothesised in H2.3. Specification 9 predicts that for a 10% increase in the level of aggregate bilateral trade shared with a recipient, donors increase the share of their finance budget allocated by 0.67%.[42]

6.2.1. Testing the impact of specifying threshold limits on finance

According to Proposition 2, the determinants of adaptation finance will change as the share of a donor's annual adaptation finance budget being considered increases. Specifically, it is predicted that the strategic considerations of donors will be stronger determinants of allocation than a recipient's level of need as the size of the share allocated increases. To test this assertion, I investigate the impact that specifying a threshold limit on the dependent variable has on the size and sign of the coefficients of the independent variables included in the specification. The results are presented in table 7. Model (12) considers all observations where a positive amount of finance classed as principal by the donor was allocated to a recipient. Model (13) restricts the sample to observations where an amount greater than 5% of the donor's annual budget was allocated.

[40] exp(-1.340/10) =0.87
[41] 1.1^-0.752=0.931
[42] 1.1^0.07=1.0067

Table 7: Exploration of the impact of setting a threshold limit on finance

Variables	(11)	(12) Dependent Variable	(13)
	ln (Significant finance)	**ln (Principal finance)**	**ln (Principal finance) where Share>5%**
Vulnerability lagged	26.13***	21.71***	11.83
	[6.097]	[5.784]	[7.950]
Vulnerability lagged squared	-24.80***	-20.80***	-10.05
	[5.602]	[5.128]	[7.030]
ln(Bilateral Trade Lagged)	0.0756*	0.0378	0.0330
	[0.0395]	[0.0384]	[0.0469]
ln(Population lagged)	0.178**	0.301***	0.0446
	[0.0837]	[0.0897]	[0.0601]
AOSIS	-0.273	-0.0299	-0.212
	[0.370]	[0.331]	[0.320]
Agree in UN	0.454	-0.145	0.490
	[0.732]	[0.885]	[0.760]
ln(distance)	-0.683***	-0.579***	-0.175
	[0.162]	[0.171]	[0.131]
Colonial History	1.630**	0.686***	-0.578***
	[0.619]	[0.228]	[0.186]
ln(GDP per capita lagged)	-0.512***	-0.257	0.140
	[0.105]	[0.164]	[0.152]
Governance readiness lagged	0.342	1.233*	-0.178
	[0.604]	[0.709]	[0.753]
Hub score lagged (std.)	0.0187	-0.00355	0.0716*
	[0.0496]	[0.0811]	[0.0403]
Social readiness lagged	-0.671	-1.669*	0.0334
	[0.719]	[0.899]	[1.045]
Economic readiness lagged	0.973	1.430**	-0.418
	[0.626]	[0.516]	[0.949]
Year Fixed Effects	Yes	Yes	Yes
Donor Fixed Effects	Yes	Yes	Yes
Observations	3,466	1,969	469
R2	0.3203	0.2480	0.7885

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

In contrast to table 6, table 7 considers the dollar amounts of finance allocated, not the share of a donor's budget. The sample size for model 12 is 1969 individual observations. The restricted sample considered in specification 13 is reduced to 469 observations. The results shown in table 7 give support for the theoretical assertion outlined in proposition 2; as funding packets increase in size, the determinants of funding allocation clearly change. Most obvious is the loss of significance in the vulnerability and vulnerability squared term in specification 13. In addition, the coefficient of the hub score (lagged) variable is positive and significant. In summary, whilst by no means conclusive, the results are indicative of a lower level of emphasis being placed on recipient need and an increased focus on donor self-interest as the relative size of the provided finance packets increases. Also included in table 7 is a restricted sample which only considers finance classed as significant (specification 11) which gives evidence that the determinants of adaptation finance allocation differ for principal and significant classed finance. Most notably, colonial history is shown to have a much lower impact on the allocation of principal classed finance. In addition, bilateral trade, whilst positive in both specifications 10 and 11, is not a significant determinant of principal classed finance.

6.3. Robustness checks

To test the robustness of results across both stages, donor fixed effects were added and standard errors clustered at the donor level were compared with their robust counterparts. To legitimise the use of fixed effects dummies in the first stage, the results from the first stage Probit regressions were compared to their LPM counterparts with fixed effects. For the most part, the estimated coefficients were similar across the two estimators. In addition, the marginal effects from the Heckman selection model were also compared with the first stage Probit results to assess overall model bias. These results, whilst showing some differentiation gave no immediate cause for concern. A comparison of the probability of receiving finance (the marginal effects) using a LPM, Logit, Probit and Heckman Selection model all estimated using time and donor fixed effects and standard errors clustered at the donor level (akin to specification 4 in table 4) is included in Appendix 9.

As only positive instances of adaptation finance allocation are considered in the second stage, the donor level clusters, some of which are small, differ in size. 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 few clusters by correcting the standard errors. It holds the regressors fixed across bootstrap replications. This procedure is carried out on specification 9. Key to this research is the relationship between vulnerability and the share of finance allocated to each selected recipient. Both the coefficients of the vulnerability (lagged) and vulnerability (lagged) squared terms remain significant at the 1% level when the wild cluster bootstrap- t correction is used. This robustness check confirms that the structure of the data in the second stage needs to be considered. The results discussed in text remain significant even when the correct standard errors are specified, however, their level of significance does change. Appendix 10 compares the P values calculated using cluster robust standard errors versus those calculated using wild cluster bootstrap corrected standard errors.

7. Discussion

This section explores some of the key results in the context of the theory, suggests policy recommendations resulting from an analysis of the findings and discusses the potential limitations of the modelling approach.

7.1. Understanding the results in the context of the theory

As is frequently discussed in the literature and in popular press (UN News Centre, 2014), aid allocation is in general reactive. When donors allocate aid in response to an event they have, for all intents and purposes, enough information to effectively evaluate the merits of aid allocation in that particular case. Adaptation as a pre-emptive measure doesn't fall within this category. The theory presented in this text offers an explanation of the highly-scattered nature of finance allocations exhibited by donors which renders a high number of recipients with particularly low shares. Given the uncertainty surrounding the occurrence of climate change impacts, and the often results driven nature of the international development sector, it is not unexpected that climate change adaptation projects tend to attract less finance than their mitigation counterparts. The theory developed in this model is well suited to explain this result empirically; see Appendix 11.

Even in a reactive sense, for example the building of a seawall in response to a storm event or changing weather patterns, the paybacks from the provision of adaptation finance are still subject to the probability of the offending storm event reoccurring in a donor specified funding period[43]. As discussed, the probability of an event reoccurring is a function of the length of that time period. There are of course cases where the provision of adaptation finance is reactive, for example the financing of a desalination plant in response to reduced water security. However, the unpredictability around weather (there being of course a distinction between climate and weather) still creates uncertainty for the donor. In such a context, the model could be adapted as follows: the probability term could be considered as the probability that rainfall above that predicted will occur in the funding period, thus negating much of the utility associated with the financing of a now defunct desalination plant (there would be a probability of (1-P) that the plant would be required within a set period). Whilst this adaptation of the model is orthogonal in many ways to the general argument presented in text; the intuition around the impact of probabilities and regret on the donor selection decision remains the same.

[43]Donors may even require an event to occur at a particular level of frequency which justifies the investment

7.2. Policy recommendations

The tendency of donors to provide bilateral adaptation finance to many countries, as found in the current research, presumably causes severe administrative costs for donors. In addition, when a recipient government tries to reach agreements with many donors, they presumably face problems caused by the conflicting conditionalities of the various donors who have provided finance (Bigsten, 2006). According to Bigsten and Tengstam (2015), by focusing on fewer countries, donors could realise significant cost savings and efficiency gains. By coordinating their aid efforts, donors could also remove any regret associated with not selecting particular recipients as funding recipients, thus increasing the likelihood of larger shares of finance being allocated to individual recipients. A key issue with the smaller packets of finance provided is their effectiveness. The recommendation for donor coordination echoes the 2005 Paris Declaration on aid effectiveness and the subsequent follow-up agreements, in which donors agreed on greater donor coordination to improve aid efficiency and effectiveness (OECD 2008).

7.3. 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 which address very different (and sometimes contradictory) issues; i.e. water security vs. flooding. By aggregating projects into yearly allocations from donor to recipient, the level of granularity associated with project specifics is unobservable. As the ND-GAIN vulnerability index considers six sectors (food, water, health, ecosystem services, human habitat and infrastructure) in its calculation, there is scope to match sector vulnerability with project level data; a significant undertaking that was not considered for this thesis.[44] It is expected that in so doing, the accuracy of results would be much improved as the level of noise in the data would be markedly reduced. There are surely cases where the level of vulnerability a country has in each sector is markedly different. The direction of bias introduced because of this 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 is a major concern in this analysis. Ellis and Moarif (2016) argue that there are inconsistencies between what countries “count” as climate finance. This means that different national reports of climate finance in the context of the USD 100 billion goal are not always comparable, complete or consistent. This inaccuracy is expected to increase as donors expand

[44] See Chen et al. (2015) for an overview of each sector included in ND-GAIN’s vulnerability index.

their annual commitments to meet the target of mobilising 100bn/year in climate finance unless a major reform in the reporting of the adaptation marker takes place. Inaccurate categorisation introduces a bias into the analysis. Junghans and Harmeling (2010) found significant evidence for over coding in the OECD CRS dataset concluding that 65 % of the projects examined were classified as inappropriately coded not having adaptation as a significant or principal target as compared with "GermanWatch" coding[45]. 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, but, in so doing, increase the robustness of my results. On the other hand, consistent over-coding 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 being that the magnitude of coefficients and their level of significance may be larger than 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 receptions to compensate for the limited impact of highly scattered aid allocations that renders a certain number of recipients with particularly low shares. Whilst this makes sense when considering an individual donor's aid allocation behaviour as these authors did, there is less justification to do so in the context of a three-way panel where recipients may be allocated several small packets of finance which are in sum, 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 in by no means ensure significant funding will be received.

8. Conclusion

In this paper, I explored how donors distribute bilateral climate change adaptation finance. To answer the research question, I specify a hurdle model which splits the donor's decision making process into two distinct stages; selection and allocation. By conceptualising uncertainty and subsequently regret as key elements of the selection decision, I predict that donors would seek to disperse their finance among similarly valued recipients rather than prioritising individual countries. The developed model also predicts that a donor's strategic interests would outweigh

[45] For example: Junghans and Harmeling (2010) included several examples of over coded projects including a water supply improvement project located in Iraq. The project was coded as adaptation however was judged to be not be explicitly linked to climate change as the lacking infrastructure and requirement for investment was a result of the security situation rather than a required response to climate change pressures

the emphasis placed on recipient's needs as the size of the funding packets allocated to an individual recipient increased. Both theoretical propositions have been shown to be empirically true. The majority of shares allocated by donors constitute less than 1% of their total annual adaptation finance budgets, with donors shown to value strategic determinants over indicators of recipient need as the size of the budget shares they allocate increase.

My results show that the positive relationship between vulnerability and both the selection for, and allocation of adaptation finance only holds up to a point; the relationship is clearly concave in both stages of the model. In addition, a marked difference is shown between how donors select for and allocate adaptation finance classed as 'significant' versus that classed as having a 'principal' focus on adaptation; recipient need is a stronger determinant of the latter. The implications of these results are twofold; first, as finance classed as 'significant' makes up the bulk of allocated finance, an increase in the total amount of funding provided shouldn't be expected to increase the amount of funding flowing to the most vulnerable by the same degree. Secondly, as on average the most vulnerable nations do not receive the most bilateral climate finance, there is a need for multilateral organisations and climate funds to fill this gap.

Suggestions for future studies include the linking of project level data to the appropriate component of the disaggregated vulnerability index (by sector). In addition, to allow a Heckman selection model to be specified, efforts to identify an appropriate exclusion restriction could be made. An alternative approach to the current research would be to follow that taken by Clist (2011) in which each donor is considered individually, thus allowing donor specific conclusions to be reached.

In conclusion, the new certainty is uncertainty about the future (Dessai, 2004). The ambiguity surrounding climate change impacts, the multifaceted nature of vulnerability, and the varying time scales of climate impacts make donor decisions regarding the selection of recipients for funding, and the amount of funds to allocate, fraught with uncertainty. Greater donor coordination can help to overcome the risk and regret associated with a donor prioritising individual recipients. In so doing, increased donor coordination could help to ensure that the most vulnerable countries receive a proportionate share of the available funds.

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10. Appendices

Appendix 1 – Activities which qualify as having a principal focus on adaptation

The scoring system for climate markers developed by the OECD consists of a three-tier system wherein a funded activity qualifies as 'principal' and receives a score of two 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 classed as having a 'significant' focus on climate change and be awarded 1 point. Projects with no focus on adaptation receive 0 points. The adaptation marker forms part of the OECD's broader Rio Marked environmental classification system introduced in 2010.

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

Examples include:

- **Enabling Activities**: Enabling activities such as improving weather and climate information systems or supporting the development of climate change adaptation-specific policies, programmes and plans.
- **Policy and legislation projects** that would qualify as having a principal focus on climate change adaptation include the strengthening the capacity of national institutions, including Finance and Planning Ministries, responsible for coordinating and planning adaptation activities and 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 including the monitoring and management of hydrological and meteorological data for decision making on impacts of climate change (and strengthening capacity for integrated planning and management of water resources could also qualify as 'principal' level projects
- **Forestry and Fisheries:** 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 the restoration of former forest areas utilising natural seed banks and existing plants, in order to reduce vulnerability to the impacts of climate change are further examples of principal level projects.
- **Health**: Developing or enhancing systems for monitoring drinking water, food and air quality, in areas affected by higher temperatures, floods and rising sea level; strengthening food safety regulations, notably in terms on microbiological quality, avoidance of contact with pest species, conservation duration and conservation temperatures, in areas affected by higher temperatures.
- **Energy:** strengthening of energy transmission and distribution infrastructure to cope with the impacts of climate change; design and construction of measures to protect critical energy infrastructure from the impacts of floods and storms.
- **Coastal Zone** Protection: 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.

Appendix 2 – Assumptions regarding the incorporation of EUT into the model

Incorporating EUT into the model requires certain assumptions to be met, EUT assumes that decision makers choose between uncertain prospects by comparing their expected utility value which is equal to the probability of each prospect occurring multiplied by the utility eventuating from that outcome. In the context of climate change adaptation finance allocation, the application of EUT assumes that donors order recipients in terms of their preferences, the order of preferences is transitive i.e. if recipient A is preferred to recipient B and recipient B is preferred to recipient C then recipient A is preferred to recipient C. It is assumed that donors know the utility resulting from the provision of finance to any and all recipients; this is akin to saying donors know the intensity of their preferences. It is assumed that donors investigate all potential recipients and compare the expected utility resulting from each of them. Finally, it is assumed that donors, as rational actors, select a subset of recipients whose combination of attributes results in the highest expected utility (Mesquita, 1988).

As discussed by Shaw and Woodward (2008), EUT models are especially credible when probabilities are very well understood and clear to the decision maker. When the subjective risks perceived by the public (or politicians) differ from those of the experts, conflict can arise. As such, donor attitude towards climate change and donor confidence in the construction methodology of the climate scenarios or vulnerability indexes is theorised to play a key role in the relationship between vulnerability and the amount of finance pledged.

Whilst this current paper uses expected utility theory to explore adaptation finance allocation under uncertainty, Osberghaus' (2015) contribution brings attention to the need to consider the subjective uncertainty which surrounds climate change scenarios. Osberghaus' (2015) argued that uncertainty around climate change predictions affects donor decision making. Using prospect theory, he explored how moving away from expected utility theory and the assumption of homo economicus can help researchers understand individual's (and individual actor's) responses to climate change. Especially relevant to this current study is the notion that evaluations of outcomes are reference dependent, and that perceived certainty of outcomes is a determinant of action or inaction (Osberghaus, 2015).

Appendix 3 – Graphical representation of proposition 1

Figure 6 shows a graphical representation of Proposition 1. It is assumed that $z_r = 0.1 * (i_r)$. Under this scenario, $P_{nt}(i_{nt})$ would have to be approximately 20% less than $P_{mt}(i_{mt})$ for the donor to choose to fund recipient m over funding both recipients m and n as shown below. In this graphical representation, it is assumed that initially $P_{mt}(i_{mt}) = P_{nt}(i_{nt}) = 0.5$

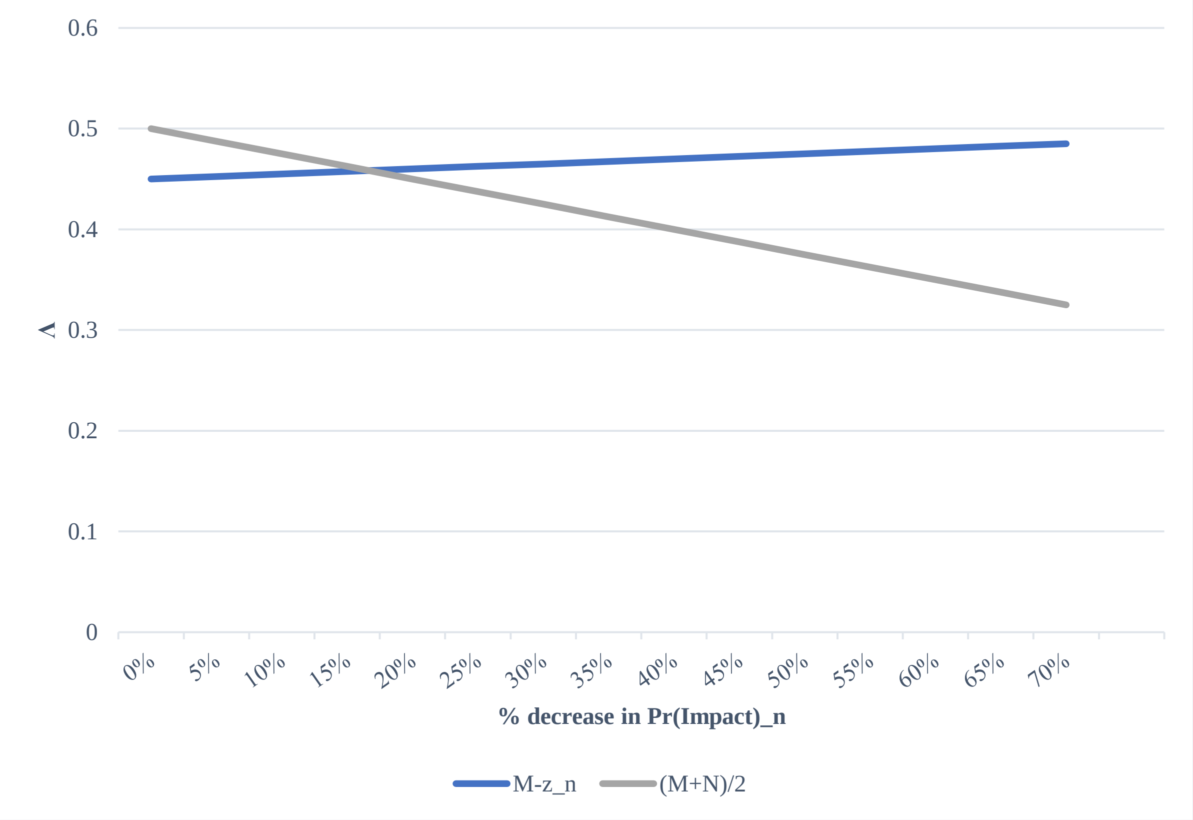

Figure 6: Graphical representation of proposition 1

Appendix 4 – Complete donor and recipient list

Table 8: Complete Donor and Recipient List

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

Appendix 5 – Exploration of the disaggregated ND-GAIN index

Figure 7 shows the relative spread of the various components of the disaggregated ND-GAIN Index used in the current research. Of note is the concentration of 68% of all four score's observations within a 20% range (relative to the total scoring range of 0-1 for these 4 indices). This spread has implications for the expected level of dispersion of funds as predicted by proposition 1 (see Section 3.1).

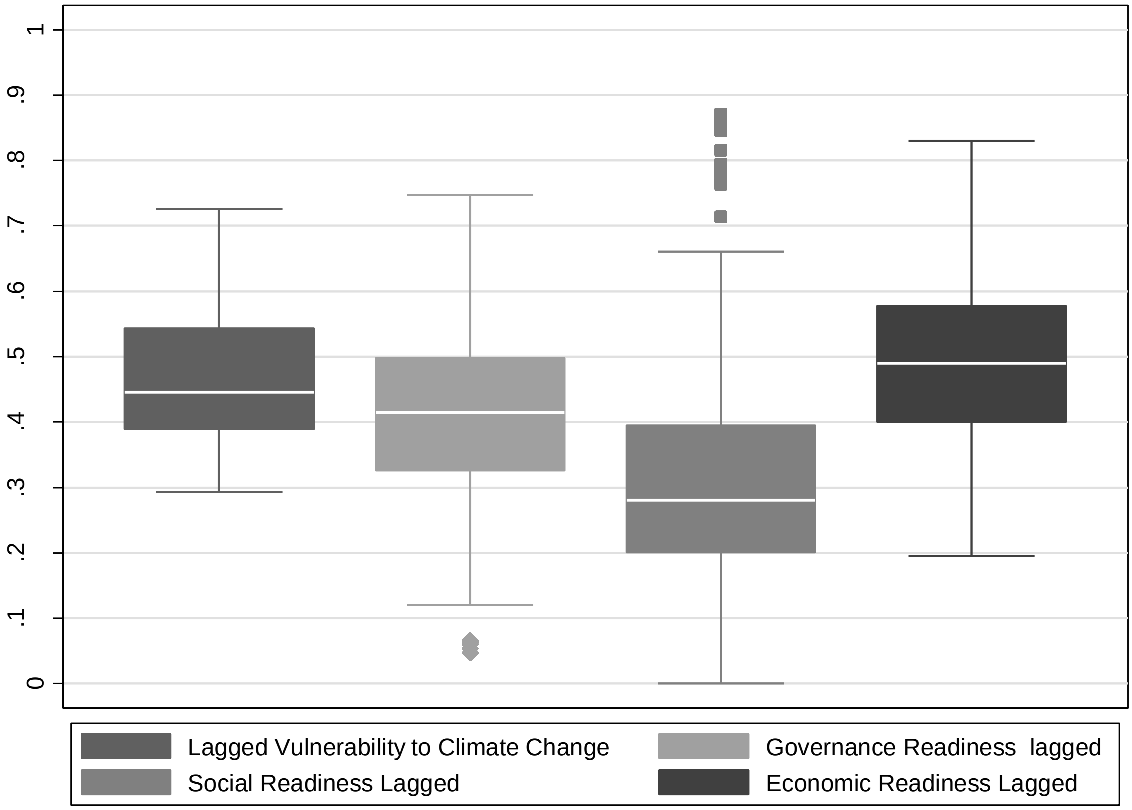

Figure 7:Box Plots of disaggregated ND-Gain Index

Appendix 6 – GDP per capita versus vulnerability by region

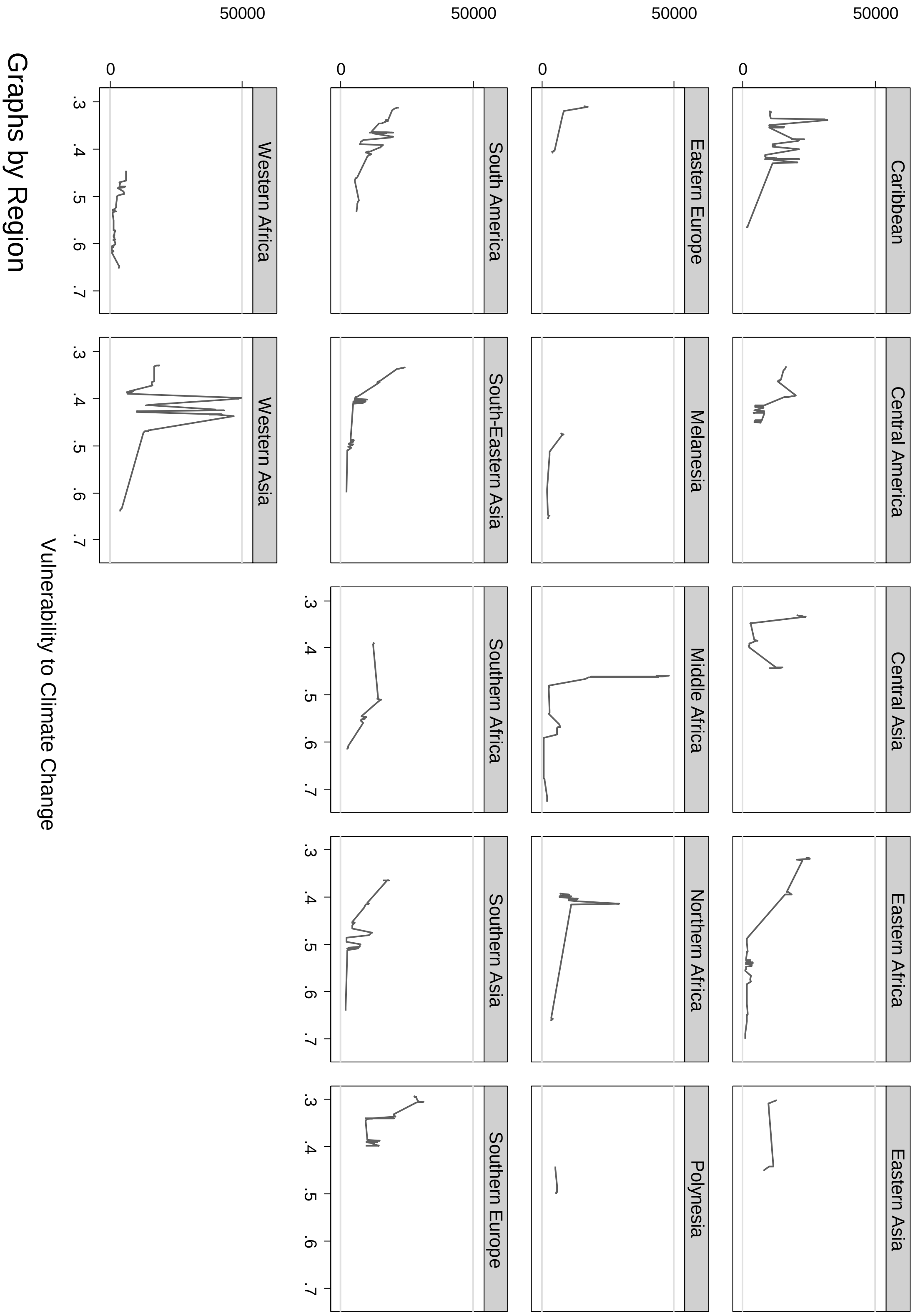

Figure 8: GDP vs. Vulnerability by region

Appendix 7 – 2015 global trade network

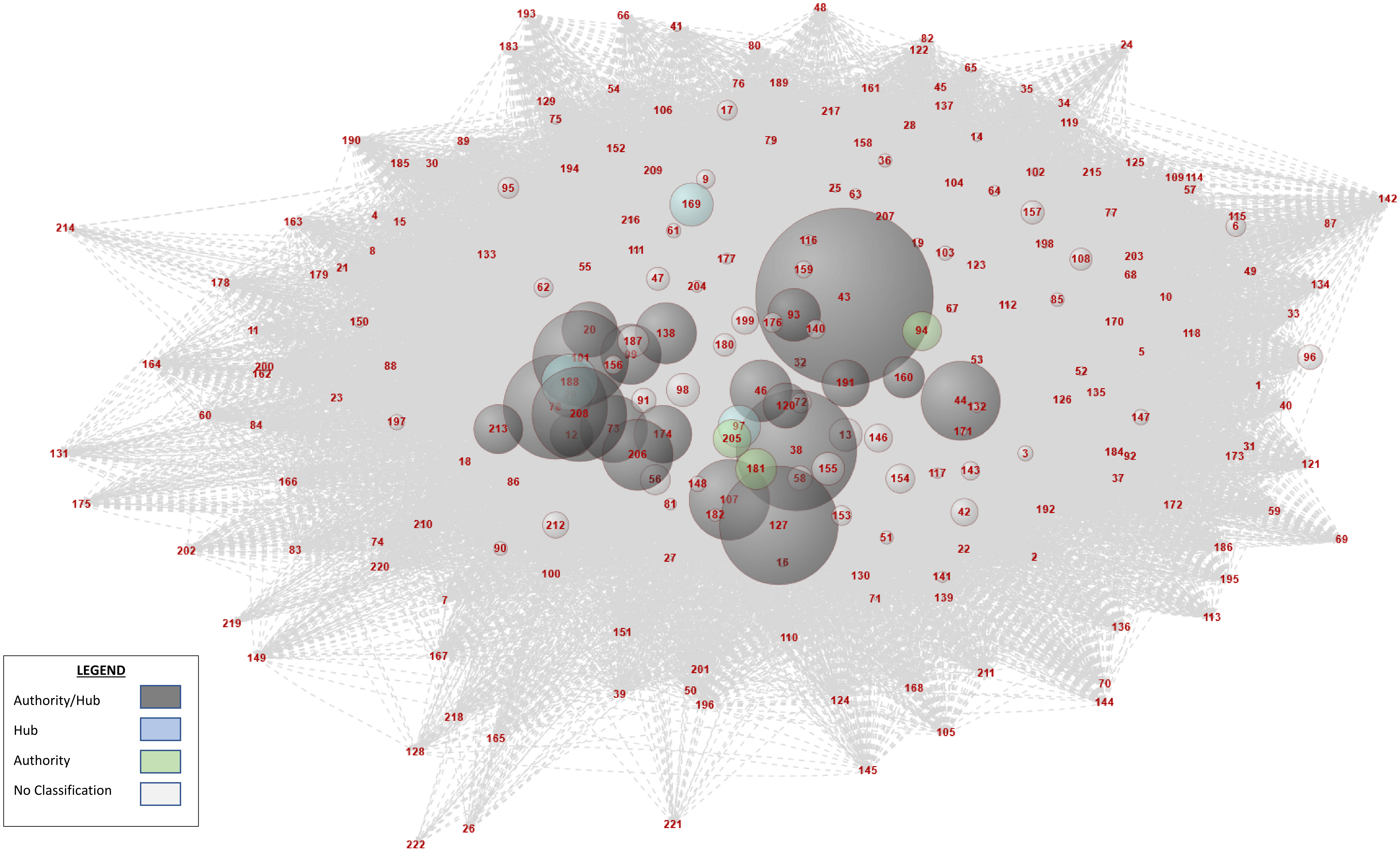

Figure 9: Global trade network (exports) for 2015

Note: Each node number represents a country; colour classification based on top subset of countries only, see overleaf for a complete list of computed hub scores for 2015 for each node. Based on export statistics sourced from UNCTADstat (2016)

Table 9: Hub Scores (2015)

Vertices	Country	Hub Weight 2015
1	Afghanistan	6.94E-05
2	Albania	2.80E-04
3	Algeria	0.00539991
4	American Samoa	9.50E-06
5	Andorra	9.49E-06
6	Angola	0.009048089
7	Anguilla	6.72E-06
8	Antigua and Barbuda	3.59E-06
9	Argentina	0.007975023
10	Armenia	2.01E-04
11	Aruba	8.70E-05
12	Australia	0.041980089
13	Austria	0.024852355
14	Azerbaijan	0.00169565
15	Bahamas	1.44E-04
16	Bahrain	0.001705267
17	Bangladesh	0.009009638
18	Barbados	7.41E-05
19	Belarus	0.002147337
20	Belgium	0.069514089
21	Belize	1.96E-04
22	Benin	2.59E-04
23	Bermuda	7.10E-06
24	Bhutan	5.14E-05
25	Bolivia	0.001679919
26	Bonaire, Sint Eustatius and Saba	0
27	Bosnia and Herzegovina	3.63E-04
28	Botswana	9.76E-04
29	Brazil	0.044588908
30	British Virgin Islands	2.50E-06
31	Brunei Darussalam	9.86E-04
32	Bulgaria	0.002336514
33	Burkina Faso	1.38E-04
34	Burundi	1.03E-05
35	Cabo Verde	4.10E-06
36	Cambodia	0.00421171
37	Cameroon	5.44E-04
38	Canada	0.329966267
39	Cayman Islands	4.57E-06
40	Central African Republic	2.62E-05
41	Chad	0.001986504
42	Chile	0.017033181
43	China (People's Republic of)	0.715497726
44	China (People's Republic of), Hong Kong SAR	0.1420433
45	China (People's Republic of), Macao SAR	2.95E-04
46	China (People's Republic of), Taiwan Province of	0.086899795
47	Colombia	0.01215323
48	Comoros	3.44E-06
49	Congo	0.001121882
50	Cook Islands	2.53E-06
51	Costa Rica	0.003984551
52	Côte d'Ivoire	0.001842553
53	Croatia	0.001061319
54	Cuba	4.16E-04
55	Cyprus	1.28E-04
56	Czech Republic	0.020556471
57	Democratic Republic of the Congo	8.41E-04
58	Denmark	0.013703542
59	Djibouti	1.20E-05
60	Dominica	2.14E-06
61	Dominican Republic	0.00479473
62	Ecuador	0.008204508
63	Egypt	0.002662787
64	El Salvador	0.002641993
65	Equatorial Guinea	0.001399252
66	Eritrea	8.30E-05
67	Estonia	0.001376491
68	Ethiopia	6.78E-04
69	Faeroe Islands	1.94E-04
70	Falkland Islands (Malvinas)	2.46E-05
71	Fiji	2.19E-04
72	Finland	0.009573202
73	France	0.102056271
74	French Polynesia	4.85E-05
75	Gabon	0.001859526

76	Gambia	1.72E-05
77	Georgia	2.24E-04
78	Germany	0.245703817
79	Ghana	0.001269109
80	Gibraltar	2.13E-05
81	Greece	0.003158605
82	Greenland	4.20E-05
83	Grenada	5.14E-06
84	Guam	3.36E-06
85	Guatemala	0.004372415
86	Guinea	2.90E-04
87	Guinea-Bissau	2.72E-05
88	Guyana	4.85E-04
89	Haiti	9.10E-04
90	Honduras	0.004399343
91	Hungary	0.0135645
92	Iceland	7.97E-04
93	India	0.063124164
94	Indonesia	0.03433576
95	Iran	0.009935977
96	Iraq	0.01406499
97	Ireland	0.040949474
98	Israel	0.024892607
99	Italy	0.082577689
100	Jamaica	5.52E-04
101	Japan	0.20718639
102	Jordan	0.001705869
103	Kazakhstan	0.004795979
104	Kenya	7.81E-04
105	Kiribati	1.04E-06
106	Democratic People's Republic of Korea	8.79E-04
107	Korea	0.146798268
108	Kuwait	0.011234753
109	Kyrgyzstan	8.47E-05
110	Lao People's Democratic Republic	4.16E-04
111	Latvia	7.90E-04
112	Lebanon	2.58E-04
113	Lesotho	3.42E-04
114	Liberia	4.62E-05
115	Libya	0.00130527
116	Lithuania	0.002668438
117	Luxembourg	0.002547435
118	Madagascar	5.26E-04
119	Malawi	1.39E-04

120	Malaysia	0.046434751
121	Maldives	4.17E-05
122	Mali	2.27E-04
123	Malta	4.32E-04
124	Marshall Islands	5.03E-06
125	Mauritania	2.34E-04
126	Mauritius	4.74E-04
127	Mexico	0.318863278
128	Micronesia	2.72E-06
129	Mongolia	0.001166993
130	Montenegro	1.72E-05
131	Montserrat	1.27E-06
132	Morocco	0.002750596
133	Mozambique	3.55E-04
134	Myanmar	0.001783664
135	Namibia	4.48E-04
136	Nauru	2.81E-06
137	Nepal	1.37E-04
138	Netherlands	0.084810398
139	New Caledonia	2.32E-04
140	New Zealand	0.008173846
141	Nicaragua	0.002804573
142	Niger	1.67E-04
143	Nigeria	0.007781029
144	Niue	0
145	Northern Mariana Islands	3.14E-06
146	Norway	0.017833491
147	Oman	0.005553284
148	Pakistan	0.005588967
149	Palau	4.63E-06
150	Panama	0.002663895
151	Papua New Guinea	0.001444341
152	Paraguay	6.88E-04
153	Peru	0.009010576
154	Philippines	0.018939124
155	Poland	0.024442644
156	Portugal	0.00797988
157	Qatar	0.012359325
158	Moldova	1.48E-04
159	Romania	0.006648462
160	Russian Federation	0.038568316
161	Rwanda	1.09E-04
162	Saint Helena	2.57E-05
163	Saint Kitts and Nevis	2.51E-05
164	Saint Lucia	5.04E-05

165	Saint Pierre and Miquelon	0
166	Saint Vincent and the Grenadines	2.42E-06
167	Samoa	4.57E-06
168	Sao Tome and Principe	1.41E-06
169	Saudi Arabia	0.042746248
170	Senegal	2.05E-04
171	Serbia	0.001098772
172	Seychelles	5.75E-05
173	Sierra Leone	1.27E-04
174	Singapore	0.075862388
175	Sint Maarten (Dutch part)	8.44E-05
176	Slovak Republic	0.008728305
177	Slovenia	0.002730968
178	Solomon Islands	8.80E-05
179	Somalia	2.54E-05
180	South Africa	0.011592789
181	Spain	0.038193047
182	Sri Lanka	0.003665111
183	State of Palestine	2.96E-05
184	Sudan	5.37E-04
185	Suriname	3.67E-04
186	Swaziland	1.19E-04
187	Sweden	0.021926934
188	Switzerland	0.072430428
189	Syrian Arab Republic	3.03E-05
190	Tajikistan	5.69E-05
191	Thailand	0.050006999
192	Former Yugoslav Republic of Macedonia	5.44E-04
193	Timor-Leste	2.11E-06
194	Togo	6.04E-05
195	Tokelau	0
196	Tonga	3.56E-06
197	Trinidad and Tobago	0.005477131
198	Tunisia	0.001694492
199	Turkey	0.01660542
200	Turkmenistan	0.002323616
201	Turks and Caicos Islands	1.43E-05
202	Tuvalu	0
203	Uganda	1.91E-04
204	Ukraine	0.003126121

205	United Arab Emirates	0.032762066
206	United Kingdom	0.113767774
207	Tanzania	6.39E-04
208	United States	0.202546117
209	Uruguay	0.001137185
210	Uzbekistan	0.001380205
211	Vanuatu	5.38E-06
212	Venezuela	0.015526206
213	Viet Nam	0.054593824
214	Wallis and Futuna	0
215	Yemen	2.09E-04
216	Zambia	8.08E-04
217	Zimbabwe	3.51E-04
218	San Marino	0
219	South Sudan	0
220	Curaçao	0
221	Holy See	0
222	Western Sahara	0

Appendix 8 – Comparison of predictive margins for selection stage

Table 10 compares the marginal effect of vulnerability to climate change on the total sample (principal + significant) with two sub samples (principal and significant) for the selection stage. The marginal effect of vulnerability is significant at the 1% level across all samples at all values. The vulnerability and vulnerability squared terms enter the model (in STATA) as an interaction term to ensure the correct marginal effects are calculated. The results are shown graphically in Figure 10.

Table 10: Marginal effect of vulnerability (lagged) on selection for different subsamples of adaptation finance

	(1) **Principal+Significant**	(2) **Principal**	(3) **Significant**
1._at 0.3	0.197***	0.0919***	0.155***
	(11.72)	(6.71)	(8.89)
2._at 0.35	0.231***	0.115***	0.187***
	(23.14)	(12.10)	(17.93)
3._at 0.4	0.253***	0.131***	0.210***
	(54.36)	(27.16)	(47.21)
4._at 0.45	0.262***	0.139***	0.221***
	(65.72)	(57.42)	(56.44)
5._at 0.5	0.257***	0.137***	0.219***
	(44.17)	(29.87)	(34.81)
6._at 0.55	0.239***	0.125***	0.205***
	(33.99)	(18.90)	(27.59)
7._at 0.6	0.208***	0.105***	0.179***
	(25.45)	(13.67)	(22.64)
8._at 0.65	0.168***	0.0806***	0.146***
	(16.37)	(10.00)	(15.60)
9._at 0.7	0.124***	0.0551***	0.107***
	(9.67)	(7.04)	(9.22)
N	17747	16484	17747

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

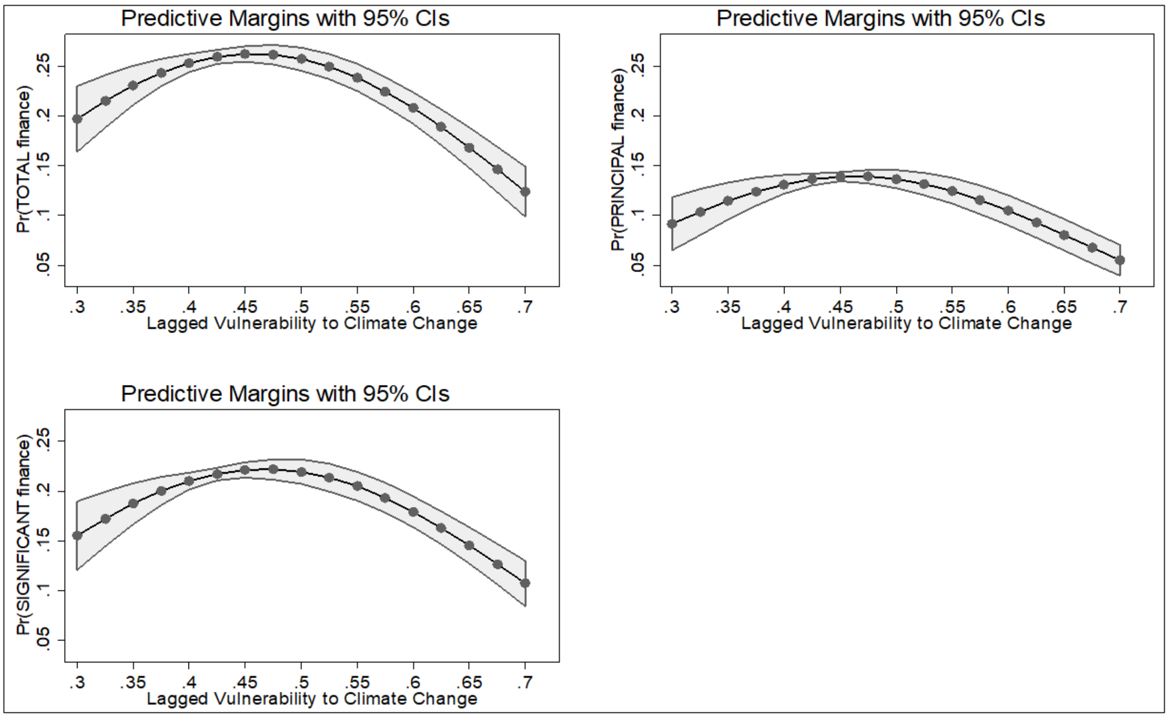

Figure 10: Predictive margins; restricted and unrestricted sample

Appendix 9 – First stage model comparison

As discussed in the text to test the legitimacy of using fixed effects dummies in the first stage, the results from the first stage Probit regressions were compared to their LPM counterparts with fixed effects as shown below (xtreg used in the case of the LPM meaning the 'within' degrees of freedom correction applied). A comparison of the probability of receiving finance (the marginal effects) using a linear, Logit, Probit and Heckman Selection model all with time and donor fixed effects and standard errors clustered at the donor level (akin to specification 4 in table 4) is included below. The similarity in magnitude and sign across the majority of the coefficients suggests no noticeable evidence of severe bias among the different estimators.

Table 11: Stage 1 estimator comparison

	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
* $p < .10$, ** $p < .05$, *** $p < .01$

Appendix 10 – Wild cluster bootstrap procedure

Because I cluster my standard errors at the donor level, I have < 30 clusters. In addition, the clusters are unbalanced as their size is a function of how many recipients each donor chose between 2011-2015. As a result, there is significant variation between clusters with some clusters being quite small. Some changes in the level of significance for certain variables is evident when the wild cluster bootstrap procedure is used (see table 12). This suggests that the fact that I have <30 (sometimes small) and unbalanced clusters in the second stage is impacting on the level of significance of my results in certain cases. Having said that, no variables completely lose their significance when the wild cluster bootstrap- t procedure is used; however, the level of significance certainly changes in some cases.

Table 12: Comparison of P Values: cluster robust vs. wild cluster bootstrap standard errors

		Cluster Robust Std. Errors	**Wild Cluster Bootstrap Std. Errors**
Variables	**Coefficients**	**P>|t|**	**P>|t|**
Vulnerability lagged	28.08	0	0
Vulnerability lagged squared	-27.00	0	0.002
ln(Bilateral Trade Lagged)	0.07	0.042	0.06
ln(Population lagged)	0.277	0.005	0.012
AOSIS	-0.13	0.667	0.63
Agree in UN	0.059	0.924	0.906
ln(distance)	-0.752	0	0.002
Colonial History	1.538	0.018	0.002
ln(GDP per capita lagged)	-0.487	0	0.002
Governance readiness lagged	1.09	0.103	0.112
Hub score lagged (std.)	0.025	0.635	0.632
Social readiness lagged	-1.340	0.058	0.07
Economic readiness lagged	1.363	0.013	0.032
Year fixed effects	Yes		
Donor fixed effects	Yes		
Observations	4,119		
R2	0.294		

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.

Appendix 11 – Comment on mitigation finance

As discussed in the text, even if the donor takes climate scenarios and their associated predictions at face value, it is logical to assume that the donor would still consider the probability of an expected event occurring within a set funding period. This is in stark contrast to the case of mitigation finance allocation in which the subjective impact of provided finance is not subjected to the same scaling effect resulting from a consideration of event probabilities, assuming the donor accepts that climate change is real.

Furthermore, donors have a greater self interest in providing mitigation finance as it is a global public good; donor's self-interest is not limited to recipient impact and strategic considerations; there exists a real payback for the donor – the reduction of global emissions. Investing in climate change mitigation projects reduces the probability that the donor will incur climate change induced damages on their sovereign land.

According to this logic and ignoring time scripts and assuming both projects are of the same monetary amount, a donor would choose to fund a mitigation project in country *m* over an adaptation project in the same country if:

$$\left(e_m + i_m^{mitigate}\right) + s_{dm} - P_m(z_m) > P_m\left(i_m^{adapt}\right) + s_{dm} \qquad \ldots \text{ (eq. 25)}$$

Where e_m represents the global impact of the resulting emissions reductions, $i_m^{mitigate}$ is the impact that the funded project has in country *m*; (for example efficiency gains in a power station, economic growth from investment and so on). With $s_{dm}, P_m(z_m)$ and $P_m\left(i_m^{adapt}\right)$ defined as before.

Removing the strategic components from the inequality results in:

$$\left(e_m + i_m^{mitigate}\right) > P_m\left(i_m^{adapt} + z_m\right) \qquad \ldots \text{ (eq. 26)}$$

As seen in the above inequality, the uncertainty associated with funding adaptation projects causes the RHS of equation 26 to be scaled by P_m, thus increasing the probability that mitigation funding will be prioritised over adaptation funding. The ratio of i_m^{adapt} to z_m has significant bearing over which project maximises the donors utility, however it is safe to assume that under a reasonable set of assumptions ($z_m < 0.2 * i_m^{adapt}$; $P_m < 0.8$) that as long as $(e_m + i_m^{mitigate}) > i_m^{adapt}$ the mitigation project will be chosen. As discussed, this outcome is likely given that mitigation represents a global public good which directly benefits the donor. Whilst the exact manifestation of e_m is unknowable, it is certain, and the actual emissions reductions are measurable. Because the emission reductions are immediately measurable and can be forecast with certainty into the future, e_m is not subject to the same timeframe constraints as i_m^{adapt}.

A key caveat to the above analysis is the existence of both an appropriate adaptation and mitigation project in the same country. An alternate explanation (or perhaps complementary explanation) to the observed donor preference for mitigation projects may be that countries which tend to have suitable mitigation projects are more attractive to donors than those which don't.