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Distributive justice in global climate finance – Recipients' climate vulnerability and the allocation of climate funds

Md. Mofakkarul Islam

Natural Resources Institute (NRI), University of Greenwich, Medway Campus, Central Avenue, Chatham Maritime, Kent ME4 4TB, UK

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ABSTRACT

The 'climate justice' lens is increasingly being used in framing discussions and debates on global climate finance. A variant of such justice – distributive justice – emphasises recipient countries' vulnerability to be an important consideration in funding allocation. The extent to which this principle is pursued in practice has been of widespread and ongoing concerns. Empirical evidence in this regard however remains inadequate and methodologically weak. This research examined the effect of recipients' climate vulnerability on the allocation of climate funds by controlling for other commonly-identified determinants. A dynamic panel regression method based on Generalised Method of Moments (GMM) was used on a longitudinal dataset, containing approved funds for more than 100,000 projects covering three areas of climate action (mitigation, adaptation, and overlap) in 133 countries over two decades (2000–2018). Findings indicated a non-significant effect of recipients' vulnerability on mitigation funding, but significant positive effects on adaptation and overlap fundings. 'Most vulnerable' countries were likely to receive higher amounts of these two types of funding than the 'least vulnerable' countries. All these provided evidence of distributive justice. However, the relationship between vulnerability and funding was parabolic, suggesting 'moderately vulnerable' countries likely to receive more funding than the 'most vulnerable' countries. Whilst, for mitigation funding, this observation was not a reason for concern, for adaptation and overlap fundings this was not in complete harmony with distributive justice. Paradoxically, countries with better investment readiness were likely to receive more adaptation and overlap funds. In discordance with distributive justice, countries within the Sub-Saharan Africa and South Asia regions, despite their higher climatic vulnerabilities, were likely to receive significantly less adaptation and overlap fundings. Effects of vulnerability were persistent, and past funding had significant effects on current funding. These, coupled with the impact of readiness, suggested a probable Low Funding Trap for the world's most vulnerable countries. The overarching conclusion is that, although positive changes have occurred since the 2015 Paris Agreement, considerable challenges to distributive justice remain. Significant data and methodological challenges encountered in the research and their implications are also discussed.

1. Introduction

In a climate change conference on 3rd March 2021, the Right Honourable Alok Sharma, President of the COP26, the 26th UN Climate Change Conference, said,

> *"Unless we get finance flowing, we cannot and will not see the action we need, to reduce emissions, to adapt, and to rise to the growing challenges of loss and damage"* (Mott McDonald et al., 2021, p.1).

Indeed, climate finance is a crucial challenge facing transitions towards a climate-resilient and low-carbon global future. Apparently, trillions of dollars will be needed to make such transitions a reality (Yeo, 2019). For instance, an IPCC report estimated the need for an annual average additional investment of US$ 830 billion between 2016 and 2050 to limit global warming to 1.5 ^{0}C by 2100 (Masson-Delmotte et al., 2018). For adaptation, the IPCC's 5th Assessment Report estimated the cost to range from US$70 to 100 billion per year (Chambwera et al., 2014), whereas the UNEP estimated such costs to be US$140–300 billion per year by 2030, and US$ 280–500 billion per year by 2050 (UNEP, 2016).

Apart from the obvious challenge of raising these titanic sums, progress in international climate finance hinges on resolving several key questions: Who is responsible for providing funding? How should funding be allocated and based on what criteria? What should the

E-mail address: m.m.islam@greenwich.ac.uk.

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funding be used for? How decisions regarding the raising, allocation, and use of climate finance are to be made and by whom? The lens of 'climate justice' is increasingly being used in framing debates and discussions on these questions, underpinned by an expectation that such a justice-based approach would improve the legitimacy of the international climate finance regime, promote consensus and collective action, and thus make international climate policies more successful (Adger et al., 2006; Baatz, 2018; Ciplet et al., 2013; Colenbrander et al., 2018; Gardiner, 2004; Gifford & Knudson, 2020; Grasso, 2010; Khan et al., 2020).

In relation to the foregoing questions, several facets of justice are used in the climate finance literature. However, the one that provides the impetus for this article is 'distributive justice'. Like any notion of 'justice', this term can be contentious, depending on who defines it and based on what philosophical, moral, ethical, normative, and/or legal standards. A comprehensive take on the concept is beyond the scope of this article and can be found elsewhere (see Ciplet et al., 2013; Grasso, 2010; Khan et al., 2020). In a nutshell, it centres on two main issues – the 'raising' and 'allocation' of adaptation funds. Regarding the first, it is argued that, developed countries, who have historically benefitted from a high-carbon economy, and thus have contributed disproportionately highly to climate change, have a burden (the so called 'climate debt') in helping developing countries finance adaptation (Gifford & Knudson, 2020; Khan et al., 2020). Thanks to decades of debates, discussions, and negotiations, this obligation has now been recognised in multiple climate agreements, including the UN Framework Convention on Climate Change (UNFCCC), the Kyoto Protocol, the Marrakech Accord, the Copenhagen pledge, and the Paris Agreement (see Khan et al., 2020 for a useful review). The second issue, also now codified in various agreements, concerns the allocation of adaptation funding to countries that are 'particularly vulnerable' to climatic changes, as emphasised, for example, in articles 3 and 4 of the UNFCCC, and articles 7, 9, and 11 of the Paris Agreement (UN, 1992; UN 2015). Nevertheless, the implementation of these principles has been replete with challenges, arousing considerable debates and tensions.

This article focuses on the second (i.e., allocation) principle, the practice of which has been of widespread and ongoing concerns (Ciplet et al., 2013; Khan et al., 2020; Mott McDonald et al., 2021; Watson & Schalatek, 2019). As a recent example, it is worth quoting the COP26 President, who, in the aforementioned conference, stated,

> *"Finally, a major concern on [climate] finance is improving accessibility. …… An indicator of the current state of affairs is the low level of finance making its way to the most vulnerable nations"* (Mott McDonald et al., 2021, p.7).

The empirical foundation of such long-standing concerns, however, appears to be still weak. Even though many studies have investigated the determinants of adaptation finance allocation (Betzold & Weiler, 2017; Chen et al., 2018; Doshi & Garschagen, 2020; Mori et al., 2019; Persson & Remling, 2014; Robertsen et al., 2015; Robinson & Dornan, 2017; Weiler et al., 2018; Weiler & Sanubi, 2019; Weiler & Klock, 2021), only a few (Betzold & Weiler, 2017; Doshi & Garschagen, 2020; Persson & Remling, 2014; Weiler et al., 2018) had vulnerability as their primary focus. Of the latter, only two studies (Betzold & Weiler, 2017; Weiler et al., 2018) quantified and compared the effects of vulnerability between the 'most vulnerable' countries and the others.

The results of these studies have been mixed, with some authors (Betzold & Weiler, 2017; Weiler et al., 2018) reporting vulnerability to have a positive effect on adaptation funding, whilst others reporting no effect (Persson & Remling, 2014; Robertsen et al., 2015) or a minor, secondary effect (Doshi & Garschagen, 2020). Quantification of the effects of vulnerability also appeared inconsistent, with some authors finding the "most vulnerable countries" likely to receive 0.3–0.5% more adaptation funds (Betzold & Weiler, 2017, p. 31), whereas others (Weiler et al., 2018, p. 72) reporting the increment to be 60–300%. It is also unclear if the relationship between vulnerability and funding allocation is perfectly linear, or there is a limit beyond which vulnerability may work to the disadvantage of a recipient country.

Moreover, all of these studies, except Weiler and Sanubi (2019), investigated the effect of recipients' vulnerability on adaptation funding only. Although such a focus is understandable, since 'adaptation' by definition is linked with 'vulnerability reduction', it does have significant limitations in providing inferable evidence regarding distributive justice. Adaptation and mitigation activities, for example, may not always be distinguishable (Chandler et al., 2002), of which the so-called 'Nature-Based Solutions' (Austin et al., 2021) can be a classic example. It is perhaps because of this reason that some donor institutions, e.g., the OECD-DAC, classify climate finance into three categories: mitigation, adaptation, and overlap (Simon, 2018). Assessing the effects of vulnerability on such overlap funding is therefore important for getting a complete picture of distributive justice.

A focus on mitigation funding is important in consideration of the historical contexts surrounding the emergence of and struggle for adaptation finance (Ciplet et al., 2013; Khan et al., 2020). Historically, developed country Parties have been more inclined to funding mitigation than adaptation. Developing country Parties, while not denying the importance of mitigation funding, have bargained more for adaptation funding. At the heart of this adaptation funding politics lies the argument that the world's poor (and hence vulnerable) developing countries have historically been the least emitters of greenhouse gases, and yet, have been the worst victims of global climate change (Ciplet et al., 2013). Preventing and safeguarding from the harmful impacts (e.g., loss of lives and livelihoods) of climatic changes, rather than reducing emissions, is thus atop their priorities. Allocation-based distributive justice, if defined from such recipient's need perspective, would then demand a decoupling between vulnerability and mitigation finance. Such an expectation is not untenable as landmark documents, such as the UNFCCC and the Paris Agreement, emphasise on climate financing to be responsive not only to the 'particularly vulnerable' developing countries but also to the 'specific, urgent, and immediate needs as well as the special circumstances' of such countries (see UN, 1992, Article 3.2; UN 2015, Articles 7.2, 7.6 and 9.4). A key purpose of such responsiveness, e.g., as stated in the Paris Agreement, is to "protect people, livelihoods, and ecosystems" (see UN 2015, Article 7.2, p. 9). Realities on the ground, however, raise potential cause for concern. Adaptation finance continues to remain disproportionately lower than mitigation finance (Mott McDonald et al., 2021; Yeo, 2019), although the overall flow of finance has increased over the years (Yeo, 2019). Is it possible then that the world's vulnerable countries, despite their historical struggles for more adaptation funding, are still provided with more mitigation funding? If the answer is 'yes', then what may be the reason(s) and what would it mean for distributive justice? Answering these questions is important for a nuanced and more complete understanding of distributive justice in global climate finance.

Methodologically, all previous studies, except a few, used aggregated funding data without considering yearly variations in funding. The panel data studies (Betzold & Weiler, 2017; Weiler et al., 2018) covered short, four-six year funding periods, which were not amenable to robust econometric methods – a limitation acknowledged by the authors themselves (Betzold & Weiler, 2017). Moreover, all previous studies used 'static models' by ignoring the 'dynamic' nature of funding allocation and did not adequately control potential 'endogeneity' in their analytical models. Confidence in the results of these earlier panel data studies, therefore, remains shaky.

Thus, the aim of this paper is to re-examine the effects of recipient countries' climate vulnerability on the allocation of three types of climate finance – adaptation, mitigation, and overlap – by using more advanced panel regression methods on a larger, more recent, and longitudinal dataset spanning two decades. The rest of the paper is structured as follows. In section 2, an analytical framework outlining the factors that may affect climate fund allocation is provided. In Section 3, the data and methods used are described. The findings are presented in Section 4. In Section 5, the findings are discussed, and key conclusions drawn.

2. Analytical framework

The non-experimental nature of this research necessitates investigating the effect of vulnerability by controlling for other potential determinants of climate funding allocation to avoid omitted variable bias. Researchers concerned with this topic commonly used a three-dimensional framework, comprising: recipient needs, recipient merits, and donor interests (see Halimanjaya 2016; Weiler et al., 2018; Weiler & Sanubi, 2019 for details).

From a **recipient need** perspective, 'vulnerability' has been a commonly-considered factor in studies on adaptation funding allocation. The underlying rationale has been discussed earlier and therefore will not be repeated here. However, although emphases are placed on providing more adaptation funding to countries that are 'particularly vulnerable' in various climate agreements, Parties have, to date, failed to agree on an operational definition of this term, primarily because of vested and competing interests (Ciplet et al., 2013; Kahn et al., 2020). Even developing countries, or their groups, themselves have locked into struggles against each other in having the term defined in a way that serves their vested interests, which Ciplet et al. (2013, p.8) have labelled as the "Wedge". The existence of such struggles, wedge, and sensitivities mean that donors may not use vulnerability as a criterion in funding allocation.

Similar challenges can be found at the finance provider level. An earlier study found that the term 'particularly vulnerable' was neither formalised, nor used as a criterion in funding allocation by the Adaptation Fund (AF) – one of the world's largest adaptation funding providers (Persson & Remling, 2014). No evidence was found that this situation has changed. Although, the AF mentions "particularly vulnerable" to be a key criterion for a country's funding eligibility (Adaptation Fund, 2017a, p.5; Adaptation Fund, 2017b, p.19), neither its operational policies and guidelines (Adaptation Fund, 2017a), nor its project review criteria (Adaptation Fund, 2017b) seem to provide measurable indicators of the 'particularly vulnerable' term. Similarly, the Green Climate Fund (GCF), another large global climate funding provider, claims to provide adaptation funding to developing countries that are "particularly vulnerable" to the adverse effects of climate change (GCF, 2020a, p.3). Its programme/project proposal review criteria include "vulnerability of the country" as a component of recipient needs (GCF, 2020b, p.3). No further guidance, however, can be found as to how such vulnerability is assessed. The existence of such ambiguities, which may well be strategic, means that analysts may not find the expected relationships between vulnerability and funding allocation.

In the academic literature, 'vulnerability' is defined in various ways (Cutter et al., 2009; Nelson et al., 2010); however, the widely-cited IPCC definition considers vulnerability as the propensity or predisposition of an entity to be adversely affected by climatic changes, including its sensitivity or susceptibility to harm, and lack of capacity to cope and adapt (IPCC 2014, p. 128; IPCC, 2007, p. 883). Operationally, vulnerability (V) may be regarded as an entity's 'exposure' (E) to climatic changes, its 'sensitivity' (S) to those changes, and its 'capacity to adapt' (AC) to those changes successfully, i.e., $V = E + S - AC$ (Hughes et al., 2012; Islam & Al Mamun, 2020). Vulnerability thus is an interdisciplinary construct, incorporating both natural (e.g., climatic processes and events) and social dimensions (e.g., adaptive capacity) of climate change impacts. It posits that an entity, despite its exposure to climatic changes, may remain unharmed if it has the requisite adaptive capacity. At the country level, such capacity may include a country's assets and infrastructure, governance quality and effectiveness, scientific robustness, and educational level of the populations (Hughes et al., 2012).

Methodological approaches to national level vulnerability assessment, however, differs considerably. As such, previous studies on adaptation funding allocation used various vulnerability measures, including the NDGAIN's Vulnerability Index, Structural Vulnerability to Climate Change Index (SVCCI), and Climate Risk Index (Mori et al., 2019; Weiler et al., 2018; Weiler & Klock, 2021). Not all of these indices conform with the IPCC's definition, e.g., the SVCCI covers the biophysical aspects of vulnerability (i.e., exposure) only. The NDGAIN index draws on the IPCC's three dimensions; however, some studies (e.g., Betzold & Weiler, 2017; Robertsen et al., 2015; Weiler et al., 2018) have used the 'exposure' dimension of this index only and considered 'adaptive capacity' as a separate variable, whilst others (e.g., Mori et al., 2019; Weiler & Klock, 2021) have used the entire composite index. The former approach is problematic as it assumes that an entity facing a climatic extreme, for example, will surely be adversely affected. This mismatches with the way 'vulnerability' is conceptualised by the IPCC (IPCC 2014; IPCC, 2007). These anomalies and a lack of coordinated methodological approach to vulnerability assessment may make it difficult for donors, or their delegated finance providers, to allocate funding based on vulnerability assessment (Ciplet et al., 2013).

Vulnerability has not been considered as a recipient need in studies on mitigation funding allocation, with Weiler and Sanubi (2019) being an exception. Some key recipient needs considered in mitigation studies are: amount of greenhouse gas emissions, rate of deforestation, and amount of carbon sinks (Bagchi et al., 2016; Halimanjaya, 2016). The underlying reasoning is that donors are likely to allocate mitigation funding to countries having greater potential to reduce emissions and deforestation. They may also be driven by prospects of profitable carbon markets (see the review by Burnham et al., 2013). Evidence are, however, mixed, with one study (Halimanjaya, 2016) reporting a significant positive effect, another (Bagchi et al., 2016) reporting a non-significant effect. Studies on adaptation funding, in contrast, have not considered these factors, probably because traditionally adaptation has been de-linked with emission reduction goals.

The above dichotomy between adaptation and mitigation funding allocation models may not always hold true. In Bangladesh, for example, restoration of the country's degrading mangrove forests (*Sundarbans*) could not only reduce emissions, but also help reduce the country's vulnerability to climate-driven sea level rise, flooding and salinity intrusions, coastal erosions, and tropical cyclones (Islam & Al Mamun, 2020; Islam et al., 2021). All these, in turn, could reduce the vulnerability of local livelihoods. Indeed, most of such 'Nature-Based Solutions' to climatic problems may have dual, overlapping benefits (Austin et al., 2021). Donors may, therefore, be motivated to allocate mitigation funding to vulnerable countries by this logic. For instance, both emission reduction and sustainable developmental outcomes are used as rationale for promoting two of the world's main mitigation mechanisms – REDD+ and CDM (Burnham et al., 2013). It is possible then that a positive effect of vulnerability may be found not only on adaptation funding but also on mitigation and overlap fundings.

The developmental status of recipients is widely considered in both adaptation and mitigation funding allocation studies. A commonly-used variable is GDP per capita used as a proxy indicator of poverty. The inclusion of this variable in adaptation funding allocation models (Betzold & Weiler, 2017; Robertsen et al., 2015; Weiler et al., 2018) makes sense, since it relates to the social dimensions of vulnerability, as explained earlier. The effect of GDP per capita on mitigation funding, however, can be complex and depend on the level of donor rationality. Rational, efficiency-driven donors may direct mitigation funding to countries with higher GDPs which may provide opportunities for greater emission reduction, given a certain amount of funding. Since very poor countries are not the biggest emitters, opportunities for such efficiency gains is limited, and therefore, mitigation funding may not go to those countries (Bagchi et al., 2016). Conversely, altruistic donors may channel mitigation funding to help low-income countries combat poverty, infant mortality, and other forms of underdevelopment (Halimanjaya, 2016). Empirical evidence, however, remains inconclusive:

Bagchi et al. (2016) found a negative effect of GDP per capita on both mitigation and adaptation aid amounts, which was similar to Mori et al. (2019) who found a negative effect of GDP per capita on adaptation aid amounts. However, other studies (Betzold & Weiler, 2017; Weiler et al., 2018) found significant positive effects of GDP per capita on adaptation aid amounts. Moreover, Halimanjaya (2016) found both positive and negative effects of GDP per capita depending on donor types, whilst Robertsen et al. (2015) found a non-significant effect on adaptation aid amount.

Population size of recipient countries is another variable considered widely by studies on both adaptation and mitigation funding allocations. The underlying reasoning is that larger countries need more support, with several studies (e.g., Bagchi et al., 2013; Halimanjaya, 2016; Robinson & Dornan 2017; Weiler et al., 2018) confirming its positive effects on both adaptation and mitigation funding.

Another variable included in previous research is the regional location of recipient countries. Countries within Sub-Saharan Africa and South Asia are considered to be more vulnerable to climatic changes, and hence, in need of more adaptation funding. Empirical evidence, however, is mixed: some studies (Weiler et al., 2018; Weiler & Klock, 2021) found that African countries were likely to receive significantly more adaptation funding than their non-African counterparts, whilst others (Betzold & Weiler, 2017; Robinson & Dornan, 2017) found no evidence of such impacts. Small Island Developing States (SIDS) status has been yet another variable of widespread interest as SIDS have been accorded priority in several climate agreements because of their higher climatic vulnerabilities (Khan et al., 2020; Robinson 2018; UN, 1992). Previous studies provide divergent evidence regarding the effect of this variable. Three studies (Weiler & Klock, 2021; Weiler et al., 2018; Robinson & Dornan 2017) found a significant positive effect, whilst two studies (Betzold & Weiler, 2017; Mori et al., 2019) found a non-significant effect of the SIDS status on adaptation funding.

Regarding **recipient merits**, a commonly-investigated factor is 'readiness'. Although the term has not been consistently defined and operationalised, it basically refers to social, institutional (including governance), and economic qualities of a recipient country. On the social front, some climate vulnerable countries may lack requisite human resources, skills, and infrastructure in order to be able to access climate funds. For example, to receive funding, a vulnerable country must be able to articulate and provide evidence of its vulnerability to funders. This may be quite challenging because of a lack of country-specific historical climate data, skilled human resources, and IT infrastructure (Chase et al., 2020; Fiala et al., 2019), as well as considerable ambiguities surrounding the terms 'climate finance', 'vulnerability', 'mitigation', 'adaptation', and 'development' (Chandler et al., 2002; Hall, 2017; Roberts & Weikmans, 2017). Such capacity deficiencies are widely noted, e.g., a recent review of 93 GCF-funded project proposals found that 80% did not have a well-defined Theory of Change (ToC), 68% did not or clearly discuss methods for measuring change, and only 10–13% included measurable indicators and/or methods for evaluating change (Fiala et al., 2019). Another recent evaluation found a lack of capacity to prepare good quality project proposals, unavailability of historical climatological data, low number of qualified staff, and lack of technical, monitoring and evaluation capacities, as key barriers to SIDS' access to GCF funds (Chase et al., 2020). Such weaknesses, in turn, may erode donor confidence on the ability of recipient countries to successfully implement and manage climate-related interventions, thus reducing their chances of getting funded (Doshi & Garschagen, 2020).

Similarly, weaknesses in governance and institutions, as well as conflicts and violence, which pervade many developing countries, may dissuade funders due to higher perceived risks of investment. Studies provide consistent evidence of the significant effects of these factors on both adaptation and mitigation funding allocations (Bagchi et al., 2016; Betzold & Weiler, 2017; Halimanjaya, 2016; Robertsen et al., 2015; Robinson & Dornan 2017; Weiler et al., 2018; Weiler & Sanubi, 2019; Weiler & Klock, 2021).

Although readiness may have multiple dimensions, some researchers (Chen et al., 2018; Mori et al., 2019) concerned with adaptation funding allocation have assessed it as a single composite variable. These studies also report a significant and positive effect of readiness on funding allocation.

It is also noteworthy that, conceptually, 'readiness' may overlap and have an inverse relationship with 'vulnerability' because of the former's similarity with the concept of 'adaptative capacity', which is an element of vulnerability (Hughes et al., 2012). This may be a potential reason why more vulnerability may not always result in more funding for recipients.

Donor interests are difficult to investigate directly because of a lack of data (Betzold & Weiler, 2017; Weiler et al., 2018). Several proxy indicators were used in previous studies. Halimanjaya (2016) found that recipients geographically closer to donors were likely to receive significantly more mitigation aids, and Weiler et al. (2018) found that former donor colonies were likely to receive significantly more adaptation funding. Donor interests may also be about trades, with studies confirming that recipient countries that imported more from donor countries were likely to receive more adaptation aids (Weiler et al., 2018; Weiler & Klock, 2021). Moreover, donors may be more willing to support those countries that depend on them, thus ensuring their continued loyalty. To account for such geopolitical interests, several proxy indicators – including total development aid, per capita ODA, and ODA proportional to GNI – were used and found statistically significant in adaptation aid allocation studies (Robertsen et al., 2015; Robinson & Dornan, 2017; Weiler et al., 2018).

3. Data and methods

3.1. Data description

Multiple datasets were combined for this research (Table 1). Data for

Table 1
Variables and data sources used in this study.

Themes	Variables	Variable codes	Measures	Data sources
Funding allocation	Mitigation funding	mitfund	Thousand US$ (2018 rate)	OECD-DAC
	Adaptation funding	adfund	ditto	ditto
	Overlap funding	overfund	ditto	ditto
Recipient need	Vulnerability	vul	Index score	ND-GAIN
	Emissions per capita	emiss	Metric tonnes CO_2	World Bank
	Population	pop	Population (headcount)	ditto
	GDP per capita	gdppc	Current US$	ditto
	HDI	hdi	Index score	UNDP
	Region: Europe & Central Asia	reg_eca	dummy	OECD-DAC
	Region: East Asia & Pacific	reg_eap	ditto	ditto
	Region: Latin America & Caribbean	reg_lac	ditto	ditto
	Region: Middle East & North Africa	reg_mena	ditto	ditto
	Region: South Asia	reg_sa	ditto	ditto
	Region: Sub-Saharan Africa	reg_ssa	ditto	ditto
	Small Island Developing States	sids	ditto	ditto
Recipient merit	Readiness	read	Index score	ND-GAIN
Donor interests	Import Index	impindx	ditto	UNCTAD
	ODA per capita	odapc	Current US$	World Bank

the study's main focus, 'allocation of climate funds', came from the OECD-DAC's climate-related funding database – one of the most comprehensive data sources of its kind and is widely used in previous studies (e.g., Betzold & Weiler, 2017; Halimanjaya, 2016; Robinson & Dornan, 2017; Weiler et al., 2018). The OECD-DAC dataset captures both bilateral and multilateral climate-related development finance flows, identified using the Rio Markers, and/or the Climate Components methodology (Simon, 2018). The data included 'approved funding' in the forms of debt instruments, equity and shares in collective investment, and grants provided by both public donors (e.g., DAC member states, multilateral development banks) and private donors (e.g., BBVA Microfinance Foundation, B&M Gates Foundation, Mastercard Foundation, various Postcode Lotteries, and other Foundations). The funding covered three types of climate-related development interventions: mitigation, adaptation, and overlap. This classification is based on a scoring system ranging from 2 to 0. A value of 2 is assigned when an aid-funded climate activity (e.g., a project) has mitigation or adaptation as the 'principal' objective, 1 when an activity has a 'significant' (but not principal) mitigation or adaptation objective, and 0 when an activity has no mitigation or adaptation objective. An 'overlap' category refers to a funded activity which has both mitigation and adaptation objectives (either principal or significant). For example, water basin management involving forest protection/reforestation for reducing the severity of floods while increasing carbon uptake may be given a mitigation score of 1 and an adaptation score of 2 (OECD, undated).

These three types of approved funds were the dependent variables of this study (Table 1). Some double entries in the OECD-DAC dataset were detected and corrected. The dataset included some funding incidents (projects) for which no specific country could be identified, e.g., funds provided to regional entities or multiple countries. These were dropped from analysis. In total, funding data for 151 countries, beginning from the year 2000 through to the year 2018, were analysable. Over these 19 years, all 151 countries received at least one of the three types of funding each year. However, the OECD-DAC database had adaptation and overlap funding data from 2010 to 2018 only. If a country did not receive a specific type of funding in a given year, funding for that specific type and year was recorded as zero.

Data on climatic vulnerability, this study's main explanatory variable of interest, were obtained from the Notre-Dame Global Adaptation Index (ND-GAIN) database, which has been used widely by previous studies (e.g., Betzold & Weiler, 2017; Chen et al., 2018; Mori et al., 2019; Robinson & Dornan, 2017; Weiler et al., 2018; Weiler & Sanubi, 2019; Weiler & Klock, 2021). The ND-GAIN data were used for the readiness variable also. As per IPCC's definition of vulnerability (Section 2), the ND-GAIN vulnerability index covers the exposure, sensitivity, and adaptive capacity dimensions of a country. Indicators of each dimension covers six sectors – food, water, health, ecosystem services, human habitat, and infrastructure. Six indicators for each sector is used, totalling 36 indicators for the vulnerability index. Consistent with the literature (Section 2), the ND-GAIN readiness index covers economic, governance (institutions), and social dimensions. Economic readiness includes the World Bank's Doing Business sub-index, whilst the governance readiness is based on four indicators: political stability and non-violence, control of corruption, rule of law, and regulatory quality. The social readiness indicators are: social inequality, ICT infrastructure, education, and innovation. For details about each indicator, their rationale, and methods used in constructing the index variables, see Chen et al. (2018). Data for the other control variables came from the OECD-DAC, World Bank, UNDP, and UNCTAD databases, as shown in Table 1.

Considerable missing values were encountered in this study. Vulnerability data for 15 of the 151 countries that received climate funding during 2000–2018 were missing, including: Cook Islands, Kiribati, Korea DPR, Kosovo, Marshall Islands, Montserrat, Nauru, Niue, Palau, St. Helena, St. Vincent & the Grenadines, South Sudan, Tokelau, Tuvalu, and West Bank & Gaza. As these data were non-imputable (i.e. not 'Missing at Random' type), these 15 countries were dropped from analysis. A further three countries had to be dropped as they had only one incident of funding and thus were not amenable to panel data methods. Thus, data for a total of 133 countries over 19 years, i.e., 2,527 observations were analysed for mitigation, and data for 133 countries over 9 years, i.e., 1,197 observations were analysed for adaptation and overlap fundings. For these 133 countries, ~2–5% values were missing for GDP per capita, HDI, ODA per capita, and emission per capita. Missing values for the first three were imputed by using the Multiple Imputation by Chained Equations (MICE) procedure (see Azur et al., 2011) with 20 iterations; however, missing values of the last variable could not be imputed.

3.2. Empirical strategy

According to the analytical framework proposed in Section 2, the models estimated in this study comprised funding allocation as a function of vulnerability, control variables, unobserved country-specific fixed effects, time fixed effects, and errors (Eq. (1)). Of the controls, emissions per capita, population, GDP per capita, HDI, readiness, import index, and ODA per capita (Table 1) were considered as time-varying, whereas regional location and the SIDS status as time-invariant dummy variables. To avoid the so called 'dummy trap', one category (Europe & Central Asia) within the region variable was dropped from analysis (taken as the reference category). Moreover, in line with others (Betzold and Weiler, 2017; Weiler et al., 2018), one year lagged values of all time-varying regressors were used in order to avoid potential reverse causality between these regressors (especially vulnerability) and the study's dependent variables. More importantly, it made practical sense as a country's vulnerability and its funding approval cannot occur at the same time. Countries have to apply first, which will be reviewed by the funder concerned before making an allocation. This process would take some time. However, unlike previous studies, this study estimated dynamic panel data models, which could be expressed mathematically as:

$$AF_{it} = \alpha + \varphi AF_{it-1} + \beta_1 V_{it-1} + \beta_2 V^2{}_{it-1} + \gamma C_{it-1} + \delta_{t-1} + \eta_i + \varepsilon_{it} \tag{1}$$

Where, AF_{it} refers to the amount of approved funding for country i (countries = 1,2,…..,133) in time t (years = 2000,……,2018 for mitigation; and years = 2010,….., 2018 for adaptation and overlap fundings); AF_{it-1} indicates the amount of approved funding lagged one year; V_{it-1} is the vulnerability score of country i in time t-1 (i.e., lagged one year); V^2_{it-1} refers to the quadratic form of vulnerability lagged one year; C_{it-1} denotes this study's time-varying control variables lagged one year as well as the time-invariant dummies; δ_{t-1} represents year dummies (lagged one year) to account for year-specific effects (e.g., global financial shock, global climate agreements) that are constant across countries; η_i represents unobserved country-specific fixed effects (errors); α is the model intercept; φ, β, γ, and δ are the vectors of coefficients estimated; and ε_{it} denotes the idiosyncratic errors

Estimating Equation (1) by a Pooled Ordinary Least Squares (POLS), Fixed-Effect (FE), or First Differencing (FD) method creates endogeneity problems due to correlations between the lagged dependent variable AF_{it-1} and η_i as well as between AF_{it-1} and the de-meaned (in the case of

FE) or first-differenced values of ε_{it} (see Roodman, 2009b for the technical details). Under the circumstances, these models produce biased and inconsistent estimates. Longer lags of the dependent variable, however, remain orthogonal to the errors and become available for use as instruments; hence, a remedy to the endogeneity issue could be, first, applying a first-difference transformation to eliminate fixed effects η_i and then using the dependent variable lagged two or more periods (e.g., $AF_{it-2}, AF_{it-3}, AF_{it-4}, \cdots$) as instruments. This so called Anderson and Hsiao (1982) estimator is consistent but not efficient as it does not utilise all available moment conditions (instruments) in the sample.

This study, therefore, used an estimator based on the Generalized Method of Moments (GMM) approach, which incorporates elements of the Anderson and Hsiao method and makes use of all available instruments (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). Besides resolving the endogeneity of the lagged dependent variable, the GMM resolves potential endogeneity issues with other regressors, including those that are not 'strictly exogenous'. For example, although 'vulnerability' has been treated as an exogenous variable in all previous studies on climate finance, this variable may not be strictly exogenous. Omitted variables, such as a sudden influx in climate-induced migration or internal displacement of people in a country in a certain year, say 2010, may attract more adaptation funding for that country in 2010 and (probably) in successive years. Those past migrations or internal displacements in 2010 (i.e. errors in an adaptation funding model), in turn, may be correlated with the 2011 and successive (future) vulnerabilities of that country, thus problematising the true exogeneity of the vulnerability variable. Similar potential endogeneity issues could be assumed for most of the time-variant regressors used in studies on climate finance. As explained earlier, de-meaning (as in FE) and first-differencing may not resolve such endogeneity problems, especially when T is not sufficiently large, with simulation studies identifying estimation bias even when $T = 30$ (Judson & Owen, 1999).

Of the two GMM variants – difference GMM and system GMM – the latter was used. Whilst difference GMM is capable of dealing with potential endogeneity issues, it's predictive capacity becomes lower when $N > T$, i.e., number of individual units is higher than that of time periods in the sample (Blundell and Bond, 1998). In such a case, the system GMM estimator performs better (Arellano and Bover, 1995; Blundell and Bond, 1998). System GMM is also robust to omitted variables, heteroscedasticity (which was the case in this study), and missing values in data (Roodman, 2009b). Moreover, it allowed estimation of the effects of the dummy variables, i.e., regions and SIDS. To estimate the models, the second generation 'xtabond2′ package in Stata version 16.1 was used (Roodman, 2009b). The consistency of the system GMM estimator was assessed by two tests. The Hansen test examined the null hypothesis that the overidentifying restrictions (i.e., instruments) used in the regressions were valid (exogenous). The second test involved testing for serial autocorrelation (AR2), with the null hypothesis being that the model errors had no serial autocorrelation. Failure to reject both hypotheses were used as evidence of the models' robustness.

Three different models of fund allocation – mitigation, adaptation, and overlap – were estimated. Because of their highly skewed distributions, the funding-related (dependent) variables (Fig. 2) were transformed by using the natural logarithm-based Inverse Hyperbolic Sine transformation (Burbidge et al., 1988; Pence, 2006). This procedure allowed retention of zero values (i.e. no funding received in a specific year), which were meaningful in this research. Moreover, consistent with previous studies (Betzold and Weiler, 2017; Weiler et al., 2018) the time variant regressors (except HDI) were also log transformed. In a dynamic panel regression, the estimated coefficients represent short-run effects. Therefore, long-run coefficients of vulnerability were estimated by dividing each vulnerability coefficient with 1-φ, where φ represents the coefficient of the lagged dependent variable AF_{it-1}.

4. Results

4.1. Descriptive results

During 2000–2018, over 104,000 projects were funded in the sampled 133 countries, with a reasonable balance between adaptation (39.66%) and mitigation (43.37%). The lowest number of projects (16.97%) was in the overlap category (Fig. 1). In terms of funding amount, however, the balance shifts more towards mitigation. Of the total US$ 434.3 billion funded over 19 years (roughly @ 22.86 billion a year), >281 billion (64.7 %) was for mitigation, >120 billion (27.67%) for adaptation, and > 33 billion (7.63%) for overlap projects (Fig. 1). This suggests that mitigation funding was more than double the amount of adaptation funding. Since 2000, funding amount increased cumulatively, with the highest amount being in 2017, followed by a decline in 2018. However, adaptation and overlap fundings began (or were recorded by OECD-DAC) since 2010 only (Fig. 1).

At the country level, considerable variations in funding amounts were found (Fig. 2). The difference in amounts between the top and the bottom recipients was so huge (e.g., 'billions' versus 'millions') that they could not even be displayed for comparison in the same graph. For example, among the top five mitigation fund recipients, the highest amount was close to 8 billion US$ in a year (India), whilst amongst the bottom five, the highest was 6 million US$ (Equatorial Guinea) only. Even amongst the top five, there were considerable between-country variations, e.g., India's funding was substantially higher than those of the others. Within a single country, considerable year-to-year variations were noted, e.g., India's total mitigation funding in the year 2014 was around 5.5 billion, declining to ~ 2.5 billion in 2015, and then rising to 5 billion in 2016 and to ~ 8 billion in 2018.

Similar between-country variations in adaptation funding were found (Fig. 2). Again, India topped the rank by securing > US$2.7 billion in 2018. In comparison, the highest amount among the bottom five was just ~ 4 million for Turkmenistan in 2011. Similar to the mitigation funding trend, considerable year-to-year variations within countries were found. Turkmenistan's funding trend for example was: 0.07 million in 2010, ~4 million in 2011, zero in 2012, 0.6 million in 2013, ~3 million in 2014, 0.06 million in 2015, 0.74 million in 2016, 0.45 million in 2017, and 1.25 million in 2018.

What has vulnerability to do with such variations in funding? Fig. 3 visualises the non-parametric relationships between funding and vulnerability. Here, the vulnerability data have been divided into 100 quantiles and each data point (dot) represents the mean funding amount within each quantile. The top three graphs show the scatterplots with connected lines between funding (logged) and vulnerability, the middle three demonstrate linear fitted lines, and the bottom three represent quadratic fitted lines. Overall, mitigation funding shows a somewhat negative relationship with vulnerability, whilst adaptation and overlap fundings show positive relationships. However, the relationships may not be perfectly linear. For example, in both mitigation and adaptation graphs, there are values showing declining funding amounts with increased vulnerability. For mitigation, the decline occurs after 50 point on the vulnerability scale, whilst for adaptation after 60 point. Linear fitted lines are distant from such values, e.g., as can be seen on the bottom right corners of the plots. In comparison, the quadratic curves look closer to those values. Although insightful, such descriptive results need further exploration as they do not consider variations within and between countries over time as well as potential estimation issues, e.g., endogeneities (see Section 3.2).

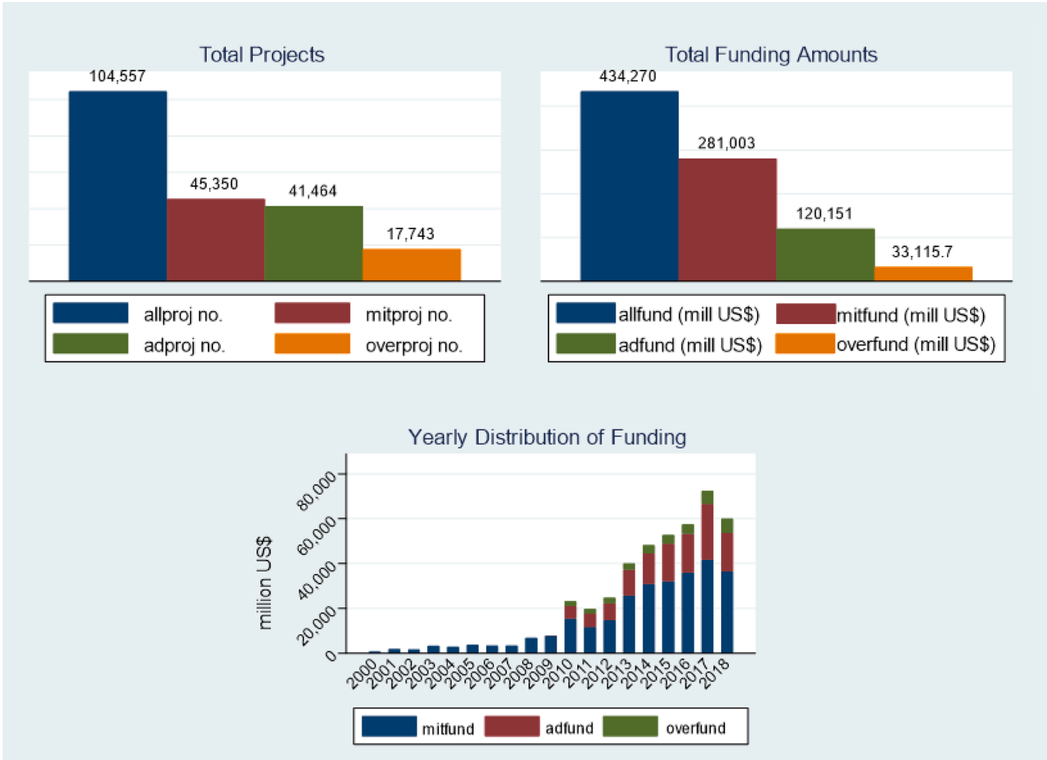

Fig. 1. Total projects, total funding amounts, and yearly distribution of funding.

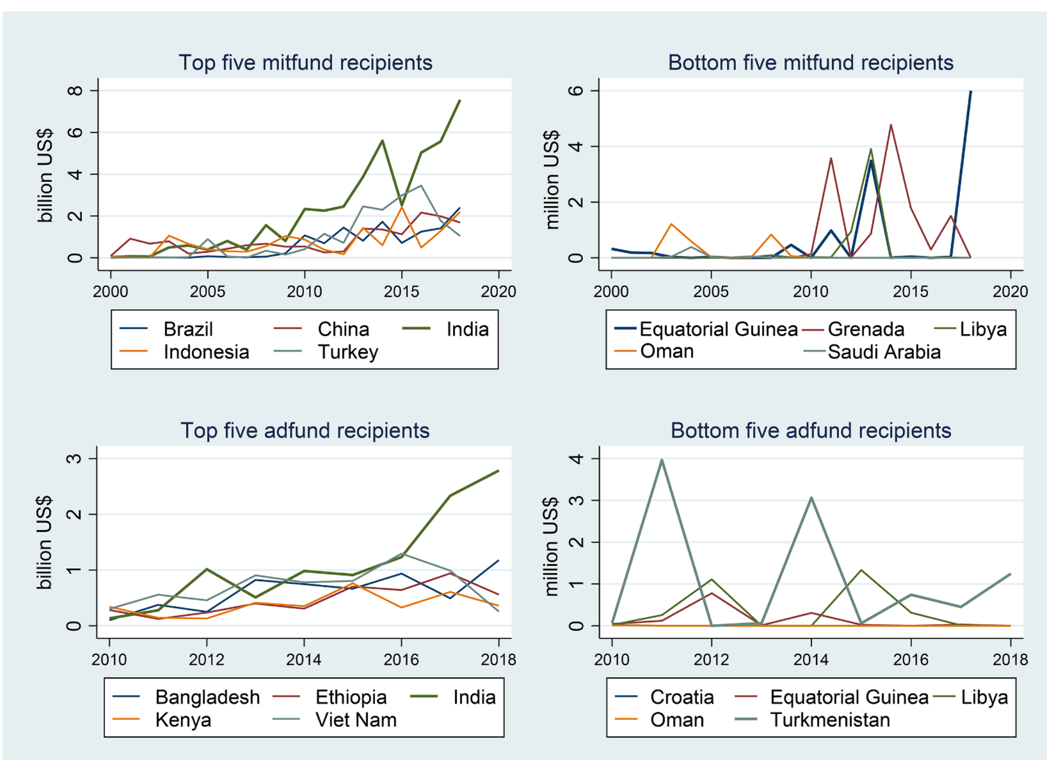

Fig. 2. Between and within-country variations in approved funding amounts (Note: length of years between mitigation and adaption funding differs because the OECD-DAC database had adaptation funding data from 2010 to 2018 only).

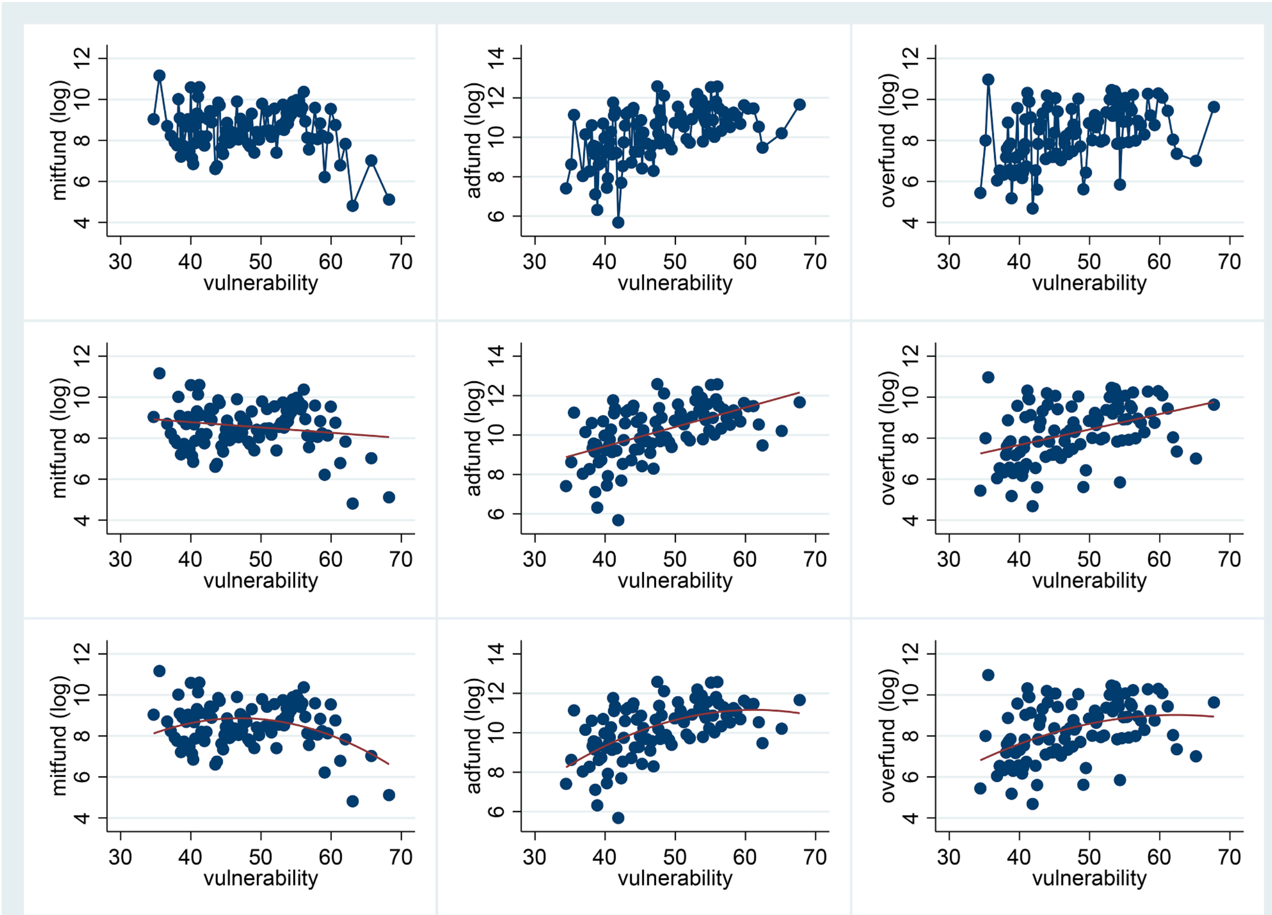

Fig. 3. Binned scatterplots showing the relationships between funding and vulnerability.

4.2. Modelling results

Panel regression results for the three types of funding – mitigation, adaptation, and overlap – are provided in Table 2. All the models showed significant effects of past funding on current funding, confirming the dynamic nature of climate finance allocation. However, the effect of past funding was negative in the adaptation fund allocation model. All the models had acceptable fitness statistics concerning serial autocorrelation (AR2) and overidentifying restrictions (Hansen J).

The vulnerability variable alone (without its quadratic effects) indicated a significant positive effect on mitigation funding, and non-significant effects on adaptation and overlap fundings (Table 2). In all the models, the quadratic effects of vulnerability were negative, confirming a non-linear (parabolic) shape of the effect of vulnerability. When these quadratic effects were considered, the Average Marginal Effects (AMEs) of vulnerability, estimated from vulnerability and vulnerability square, became non-significant in the mitigation funding model and significant ($p < 0.10$) in the adaptation and overlap funding models. The coefficients suggested that *ceteris paribus* for every one unit (on a 0–100 scale) increase in vulnerability, the amount of adaptation and overlap fundings would increase, on an average, by ~ 39% and ~ 64%, respectively.

However, given that the results confirmed the existence of non-linear effects of vulnerability, margins plots were created to understand the pattern of these effects further. As shown in Fig. 4, increased vulnerability has diminishing effects (*ceteris paribus*) on the margins (i.e. average funding amounts) of mitigation, adaptation, and overlap fundings after certain thresholds. For mitigation, it occurs after 45 point and for adaptation and overlap fundings after ~ 60 points on the vulnerability scale (in Fig. 4, a range of 30–80, rather than 0–100, has been chosen to avoid too much out-of-range prediction).

In the mitigation model, for example, the margin declines from 9.382 log units at scale point 45 to 4.234 log units at scale point 70. Moreover, the least vulnerable (point ~ 35, the lowest vulnerability score in the data, see Appendix A) has substantially higher margin than the most vulnerable (point ~ 70, the highest vulnerability score in the data). However, the highest margins are within scale points 40 and 50, i.e., it is not the least vulnerable that received the highest amount (Fig. 4).

In the adaptation funding model, the margin declines from 13.793 log units at scale point 60 to 11.467 log units at scale point 70, and in the overlap model, from 13.55 log units at point 55 to 8.18 log units at point 70. Despite such trends, however, the margins of both fundings at scale point 70 (highest vulnerability) would still be higher than those at 35 (lowest vulnerability). For example, adaptation fund margins at 70 and 35 are 11.467 and 3.611 log units, respectively. Similarly, for overlap funding, the margins are 8.180 log units at 70 and −3.382 log units at 35. Notable also is that it is the mid-range vulnerability, especially around scores 55–65 and 55–60, that are likely to fetch the highest adaptation and overlap funding amounts, respectively.

Comparisons of the adaptation and overlap funding margins with those of mitigation funding reveal further that the most vulnerable (score ~ 70) received considerably less mitigation funding (4.232 log units) and substantially more adaptation (11.467 log units) and overlap fundings (8.180 log units). Conversely, the least vulnerable (score ~ 35) received considerably more mitigation funding (8.762 log units) than adaptation (3.611 log units) and overlap (−3.382 log units) fundings. It is also noteworthy that some moderately-vulnerable countries, especially within 40–55 points, received higher or almost equal amounts of mitigation funding than the least vulnerable at point 35; however, these countries also received substantially higher amounts of adaptation and

Table 2
System GMM estimates of the funding models.

Regressors	Mitigation Fund	Adaptation Fund	Overlap Fund
ln_fund (L1)	0.231***	−0.054**	0.077**
	(17.580)	(−2.050)	(2.370)
vul (L1)	0.674**	2.144	3.944
	(2.570)	(1.640)	(1.610)
vul^2 (L1)	−0.008***	−0.018	−0.034
	(−3.160)	(−1.480)	(−1.520)
vul (AME)	−0.063	0.387*	0.637*
	(−1.010)	(1.850)	(1.890)
ln_emiss (L1)	−1.580***	0.168	0.643
	(−4.690)	(0.150)	(0.490)
ln_pop (L1)	0.888***	1.746***	2.118***
	(8.430)	(4.770)	(3.130)
ln_gdppc (L1)	0.453	0.123	1.582
	(1.600)	(0.130)	(1.150)
hdi (L1)	−3.253	4.153	−2.753
	(−0.890)	(0.510)	(−0.280)
reg_eca	ref cat.	Ref cat.	Ref. cat.
reg_eap	−0.645	−2.745	−6.021*
	(−1.210)	(−1.450)	(−1.690)
reg_lac	−1.013**	−1.104	−4.102
	(−2.620)	(−0.740)	(−1.470)
reg_mena	−1.621***	−1.871	−4.654**
	(−4.270)	(−1.600)	(−2.410)
reg_sa	−0.791	−4.711*	−9.657**
	(−1.140)	(−1.850)	(−2.200)
reg_ssa	−2.002***	−3.124*	−7.032**
	(−3.380)	(−1.710)	(−2.260)
sids	−0.050	1.828	1.441
	(−0.170)	(1.410)	(0.710)
read (L1)	0.062***	0.125*	0.122*
	(3.230)	(1.820)	(1.720)
ln_impindx (L1)	0.662***	1.233**	−0.442
	(4.580)	(2.220)	(−0.470)
ln_odapc (L1)	0.203**	0.305**	0.388**
	(2.900)	(2.290)	(2.410)
Year dummies	yes	yes	yes
Constant	−28.083***	−91.535**	−143.544*
	(−2.990)	(−2.350)	(−1.900)
F statistic	519.100***	11.74***	6.7***
No. of obs.	2,359	1,032	1,032
No. of groups	133	129	129
GMM instrument lag	9	4	4
No. of instruments	125	64	64
AR(1) p value	0.000	0.000	0.000
AR(2) p value	0.129	0.733	0.204
Hansen J p value	0.165	0.163	0.136

Estimation method: two-step System GMM
Notes: figures within parentheses are t values; *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$ (significance levels set as per previous studies on the topic and GMM modelling studies widely)
ln_fund(L1) = natural log of the funding variables with one year lag; vul(L1) = natural log of vulnerability with lag; vul^2(L1) = square of vulnerability with lag; vul(AME) = Average marginal effect of vulnerability; read(L1) = readiness with lag; ln_emiss(L1) = natural lag of per capita emission with lag; ln_impindx(L1) = natural log of import index with lag; ln_pop(L1) = natural log of population with lag; ln_odapac(L1) = natural log of Overseas Development Assistance inflow per capita with lag; reg_eca = Europe & Central Asia; reg_eap = East Asia & Pacific; reg_lac = Latin America & the Caribbean; reg_sa = South Asia; reg_ssa = Sub-Saharan Africa; sids = Small Island Developing States

overlap fundings compared to the least vulnerable.

It was also found that the effects of vulnerability were persistent in nature. The long run Average Marginal Effects (AMEs) of vulnerability on all the three types of funding (Table 3) were very similar to those in the short run (Table 2), including the direction of the effects. Moreover, the effects slightly decreased for adaptation funding (0.02) but increased for overlap funding (0.05) in the long run (Table 3).

Of the control variables, per capita greenhouse gas emission revealed, unexpectedly, a significant negative effect on mitigation funding but had non-significant effects on adaptation and overlap fundings (Table 2). The effects of population was significant and positive in all the models, showing ~ 1–2% increase in funding for per 1% increase in population. GDP per capita and HDI had no significant effects in any model. LAC, MENA, and SSA regions were likely to receive significantly less mitigation funding; SA and SSA significantly less adaptation funding; and EAP, MENA, SA, and SSA less overlap funding compared to ECA (reference category). Of particular importance is the finding that significantly less adaptation funds went to SA and SSA – two of the world's most climate vulnerable regions. SIDS status had no significant effect on funding. Readiness had significant positive effects on mitigation funding at $p < 0.01$ level, and on adaptation and overlap fundings at $p < 0.10$ level. Import index had significant positive effects on mitigation and even adaptation funding, but not on overlap funding. Aid inflow had significant effects in all the three models, with the increment in funding amounts being 0.2–0.4% for every 1% increase in per capita aid. All the models revealed significant effects of 'year' on funding (not reported).

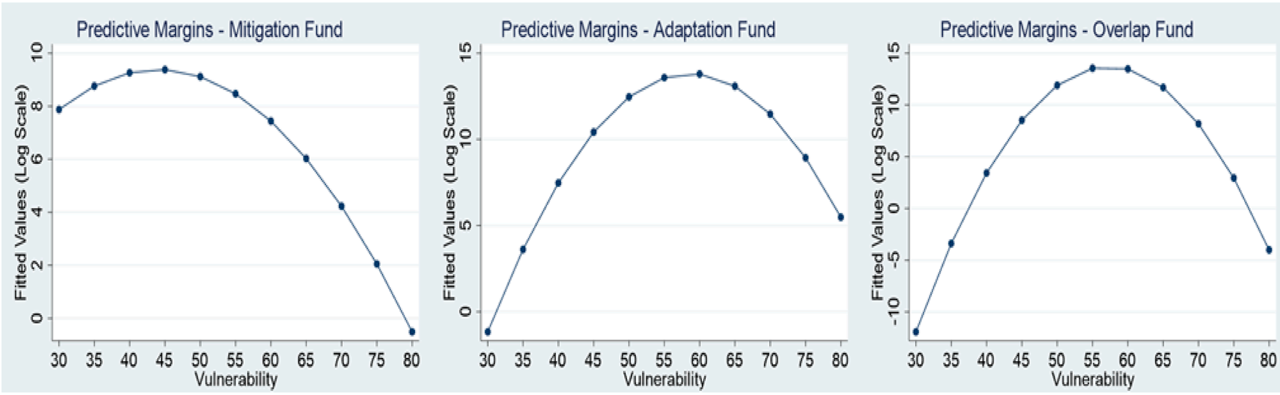

Fig. 4. Margins of funding at different levels of vulnerability.

Table 3
Long-run effects (coefficients) of vulnerability on mitigation, adaptation, and overlap funding amounts.

Vulnerability	ln_mitfund	ln_adfund	ln_overfund
Vul (L1)	0.877	2.033	4.271
Vul^2 (L1)	−0.010	−0.017	−0.037
Vul (AME)	−0.082	0.367	0.690

4.3. Robustness check

Several measures were adopted to ensure the robustness of this study's findings. A key reason why system-GMM is recommended is that the POLS and FE tend to over- and under-estimate, respectively, the coefficients of lagged dependent variables in dynamic models. Accurate estimates are expected to be between these limits (Bond, 2002; Roodman, 2009b). Accordingly, the coefficients obtained from POLS, FE, and Sys-GMM were compared. As shown in Table 4, the Sys-GMM estimates are within the expected ranges, confirming the accuracy of the estimation. Full estimates of the POLS and FE models are provided in Appendix D.

A key concern in system GMM modelling is the validity of the instrumental variables used. Non-significant p values of either Sargan or Hansen tests are commonly used to verify the validity of instruments. Sargan test works better under the assumption of homoscedasticity, which was not the case in this study, and therefore, Hansen test was used. However, it is found, including by the developer of the xtabond2 package, that Hansen p values below 0.1 and above 0.25 may indicate signs of potential trouble, with p values reaching closer to 1.0 may just be too good to be true (Roodman, 2009a). As shown in Table 2, all the models estimated have Hansen p statistics within the suggested range, indicating the validity of the instruments used.

Table 4
Robustness check – comparison of the regression coefficients of lagged dependent variables across estimation methods.

Dep Variables	POLS	FE	System-GMM
ln_mitfund (L1)	0.427***	0.0.228***	0.231***
ln_adfund (L1)	0.249***	−0.096**	−0.054**
ln_overfund (L1)	0.239***	−0.055	0.077**

Another key limitation of system GMM is its sensitivity to instrument numbers. Instrument proliferation can be a reason why system GMM models may lead to overidentification; however, lower than optimal instrument numbers may cause underidentification. The thumb rule is that instrument numbers should not exceed group numbers, which was the case in all the models of this study (Table 2). To optimise instrument numbers, two suggested techniques were adopted (Roodman, 2009a, 2009b): (i) all the models were estimated by using the 'collapse' option in xtabond2, and (ii) multiple models were estimated by using various lags and the models with minimum lags (plus maximum efficiency and acceptable AR2 + Hansen p values) were selected as the best models (see Table 2). As shown in Table 5, on the one hand, when the models were estimated with the lag numbers below those in the selected models (Table 2), Hansen p values exceeded the suggested range of 0.1–0.25. On the other hand, using more lags did not increase efficiency considerably in terms of the effect sizes of the lagged dependent variables. In fact, in some models, e.g., as in the overlap models, the efficiency declined with increased lag numbers. All these suggested that the instrument/lag numbers used in the selected models (Table 2) were optimal.

Another form of robustness check involved testing the sensitivity of the models by using a new variable, crude oil production (oilprod). The data, measured in kilo tonnes of oil equivalent, were obtained from the OECD database. Given that the descriptive statistics (Fig. 2) indicated oil producing countries like Saudi Arabia, Oman, and Libya receiving the lowest amounts of mitigation funding, it was expected that crude oil production will have a significant negative effect on mitigation funding. It was also expected that this variable will have a non-significant effect on adaptation funding as this funding is not provided for emission reduction. Inclusion of the oil production variable by replacing the emissions per capita variable confirmed these hypotheses (Table 6). The dynamic nature of funding allocation persisted in all the models as well. Moreover, the direction of effects of the other variables remained unchanged, including the expected quadratic effects of vulnerability. All the models had acceptable AR2 and Hansen p values. These confirmed that the models presented in Table 2 were robust.

Table 5
Robustness check – funding models with various lag limits and instrument numbers.

	Mitigation Fund		Adaptation Fund		Overlap Fund	
	Lag7	Lag8	Lag3	Lag6	lag3	lag6
ln_fund (L1)	0.235*** (13.400)	0.236*** (15.670)	−0.069** (−2.190)	−0.055*** (−2.730)	0.064 (1.650)	0.059** (2.360)
vul (L1)	0.662* (1.710)	0.630** (2.030)	1.346 (0.960)	2.066** (2.110)	3.346 (1.190)	2.514 (1.340)
vul^2 (L1)	−0.008** (−2.100)	−0.007** (−2.430)	−0.012 (−0.930)	−0.018* (−1.940)	−0.028 (−1.090)	−0.021 (−1.190)
vul(AME)	−0.072 (−0.900)	−0.042 (−0.580)	0.204 (0.820)	0.325** (2.130)	0.680* (1.700)	0.507** (2.010)
Ln_emiss (L1)	−1.877*** (−4.570)	−1.883*** (−5.330)	−0.991 (−0.900)	−0.432 (−0.580)	−0.062 (−0.040)	−0.658 (−0.530)
Ln_pop (L1)	0.854*** (7.300)	0.899*** (8.620)	1.639*** (4.230)	1.602*** (5.300)	1.919** (2.460)	1.569*** (3.330)
Ln_gdppc (L1)	0.708** (2.130)	0.684** (2.270)	0.371 (0.440)	0.318 (0.450)	1.891 (1.110)	1.652 (1.280)
Hdi (L1)	−3.552 (−0.850)	−1.577 (−0.410)	4.143 (0.440)	5.342 (0.870)	1.263 (0.110)	8.165 (1.020)
reg_eca	ref. cat.	ref. cat.	ref. cat.	ref. cat.	ref. cat.	ref. cat.
reg_eap	−0.772 (−1.100)	−0.912 (−1.460)	−1.892 (−0.920)	−2.049 (−1.410)	−6.396 (−1.580)	−4.021 (−1.550)
reg_lac	−1.223** (−2.480)	−1.291*** (−2.990)	−1.276 (−0.860)	−1.198 (−0.990)	−5.001 (−1.460)	−3.474 (−1.490)
reg_mena	−1.860*** (−3.660)	−1.813*** (−4.190)	−1.608 (−1.360)	−1.409 (−1.470)	−4.696** (−2.080)	−3.057** (−2.320)
reg_sa	−0.906 (−1.070)	−1.113 (−1.450)	−3.494 (−1.230)	−3.985** (−2.030)	−9.974* (−1.890)	−6.804** (−2.180)
reg_ssa	−2.070*** (−2.850)	−2.077*** (−3.170)	−2.465 (−1.230)	−2.472* (−1.710)	−7.797** (−2.240)	−4.523** (−2.180)
sids	−0.139 (−0.370)	−0.085 (−0.250)	2.655** (2.010)	1.192 (1.190)	0.731 (0.320)	0.000 (0.000)
read (L1)	0.052** (2.160)	0.057*** (2.760)	0.069 (0.910)	0.137*** (2.730)	0.102 (1.150)	0.058 (1.060)
ln_iimpindx (L1)	0.545*** (2.980)	0.600*** (4.080)	1.053* (1.990)	0.998** (2.190)	−0.742 (−0.650)	−0.205 (−0.250)
ln_odapc	0.172** (2.360)	0.168** (2.480)	0.250* (1.670)	0.366*** (3.050)	0.227 (1.170)	0.382*** (3.020)
Year dummies	yes	yes	yes	yes	yes	yes
Constant	−27.201** (−2.150)	−29.267*** (−2.790)	−64.414 (−1.460)	−87.139*** (−3.040)	−127.679 (−1.440)	−104.158* (−1.830)
F Statistic	253.06***	333.030***	13.1***	18.34***	6.540***	7.980***
No. of obs.	2,359	2,359	1,032	1,032	1,032	1,032
No. of groups	133	133	129	129	129	129
No. of instr.	**105**	**115**	**54**	**84**	**54**	**84**
AR(1) p value	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) p value	0.136	0.130	0.790	0.738	0.255	0.249
Hansen J p value	**0.042**	**0.099**	**0.642**	**0.215**	**0.428**	**0.147**

Estimation method: two-step System GMM
Notes: For mitigation funding lag9 was the selected model (see Table 2). For adaptation and overlap funding models, lag3 and lag6 are shown as lag4 was the selected model (Table 2) and lag5 was almost identical to lag4.
Figures within parentheses are t values; *p < 0.10, **p < 0.05, ***p < 0.01
ln_fund(L1) = natural log of the funding variables with one year lag; vul(L1) = natural log of vulnerability with lag; vul^2(L1) = square of vulnerability with lag; vul (AME) = Average marginal effect of vulnerability; read(L1) = readiness with lag; ln_emiss(L1) = natural lag of per capita emission with lag; ln_impindx(L1) = natural log of import index with lag; ln_pop(L1) = natural log of population with lag; ln_odapac(L1) = natural log of Overseas Development Assistance inflow per capita with lag; reg_eca = Europe & Central Asia; reg_eap = East Asia & Pacific; reg_lac = Latin America & the Caribbean; reg_sa = South Asia; reg_ssa = Sub-Saharan Africa; sids = Small Island Developing States

Table 6
Robustness check – effects of crude oil production on funding allocation.

	Mitigation Fund	Adaptation Fund	Overlap Fund
ln_fund (L1)	0.248***	−0.054*	0.089**
	(16.010)	(−1.880)	(2.570)
vul (L1)	0.844**	2.506*	3.721
	(2.560)	(1.890)	(1.510)
vulˆ2 (L1)	−0.008***	−0.021*	−0.033
	(−2.740)	(−1.700)	(−1.500)
vul (AME)	0.026	0.521**	0.517
	(0.400)	(2.080)	(1.370)
ln_oilprod (L1)	**−0.141****	**0.057**	**0.543***
	(−2.290)	**(0.260)**	**(1.830)**
ln_pop (L1)	0.462	1.150**	0.698
	(1.610)	(2.600)	(1.570)
ln_gdppc (L1)	−0.089	0.675	0.792
	(−0.350)	(0.780)	(0.830)
hdi (L1)	−1.421	3.922	−16.470
	(−0.360)	(0.370)	(−1.660)
reg_eca	ref. cat.	ref. cat.	ref. cat.
reg_eap	0.999**	−2.891	−4.974
	(2.050)	(−1.520)	(−1.430)
reg_lac	0.828**	−1.058	−2.036
	(2.000)	(−0.820)	(−0.960)
reg_mena	−0.568	−1.960	−4.308**
	(−1.100)	(−1.540)	(−2.540)
reg_sa	0.477	−4.666*	−6.515
	(0.680)	(−1.860)	(−1.660)
reg_ssa	−0.985*	−3.555*	−6.470**
	(−1.920)	(−1.980)	(−2.120)
sids	−2.592**	−1.334	−0.668
	(−2.250)	(−1.600)	(−0.900)
read (L1)	0.075***	0.188**	0.259***
	(2.970)	(2.630)	(2.720)
ln_impindx (L1)	0.808***	0.577	0.268
	(5.000)	(0.920)	(0.340)
ln_odapc (L1)	0.214**	0.386***	0.403**
	(2.520)	(3.150)	(2.600)
Year dummies	yes	yes	yes
Constant	−28.024***	−96.057**	−109.255
	(−2.860)	(−2.480)	(−1.550)
F Statistic	174.440***	12.17***	12.36***
No. of obs.	2,359	1,032	1,032
No. of groups	133	129	129
GMM instrument lag	9	4	4
No. of instruments	124	65	65
AR(1) p value	0.000	0.000	0.000
AR(2) p value	0.097	0.751	0.155
Hansen J p value	0.130	0.273	0.118

Estimation method: two-step System GMM
Notes: figures within parentheses are t values; *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$
ln_fund(L1) = natural log of the funding variables with one year lag; vul(L1) = natural log of vulnerability with lag; vulˆ2(L1) = square of vulnerability with lag; vul(AME) = Average marginal effect of vulnerability; read(L1) = readiness with lag; ln_oilprod(L1) = natural lag of crude oil production (kilo tons of oil equivalent) with lag; ln_impindx(L1) = natural log of import index with lag; ln_pop(L1) = natural log of population with lag; ln_odapac(L1) = natural log of Overseas Development Assistance inflow per capita with lag; reg_eca = Europe & Central Asia; reg_eap = East Asia & Pacific; reg_lac = Latin America & the Caribbean; reg_sa = South Asia; reg_ssa = Sub-Saharan Africa; sids = Small Island Developing States

5. Discussion and conclusions

Amidst widespread concerns (Ciplet et al., 2013; Khan et al., 2020; Mott McDonald et al., 2021; Watson & Schalatek, 2019), but weak empirical evidence, about distributive justice in international climate finance, this research aimed to examine the effect of recipients' climatic vulnerability on the allocation of climate funds. Uniquely, this research used a panel dataset containing two decades of climate funding in over 130 countries covering three areas of climate action – mitigation, adaptation, and overlap.

Unlike several previous studies (Persson & Remling, 2014; Robertsen et al., 2015; Stadelmann et al., 2014) this study revealed a significant positive effect of vulnerability on both adaptation and overlap funding allocations. This mismatch may be explained by the fact that all these earlier studies were carried out or utilised data before the 2015 Paris Agreement (PA), in which adaptation received more emphasis compared to earlier climate negotiations. The finding of this study may, therefore, be indicative of positive changes in the post-PA era. This reasoning is reinforced by successive post-PA studies (e.g., Betzold & Weiler 2017; Chen et al., 2018; Mori et al., 2019; Robinson & Dornan 2017; Weiler & Klock, 2021; Weiler & Sanubi, 2019) reporting similar findings to this study, thus providing evidence of distributive justice, according to the academic interpretation of the term (Ciplet et al., 2013; Grasso, 2010; Khan et al., 2020). Although the observed positive effect of vulnerability on overlap funding is unique to this study, it can be extrapolated as evidence of distributive justice, since overlap funding includes adaptation components (OECD, undated). The inclusion of the overlap funding type in this research, therefore, provides more comprehensive evidence of distributive justice compared to previous studies.

An examination of the effect of vulnerability on mitigation funding, alongside on adaptation funding, produced complementary evidence. The observed non-significant effect suggests that mitigation funding allocation (during the 2000–2018 period) was not driven primarily by recipients' vulnerability. This finding, coupled with the observed positive effects of vulnerability on adaptation funding, nullifies any potential concern regarding donors' greater inclination towards financing mitigation than adaptation in the world's climate vulnerable developing countries who have historically demanded and struggled for more adaption funding (Ciplet et al., 2013; Khan et al., 2020). As detailed in Section 1, the key reason behind such struggle is that climate vulnerable developing countries have historically been the least emitters of greenhouse gases, and yet, have been the worst victims of global climate change. Therefore, although both mitigation and adaptation funding are important for such countries, the latter should be prioritised, as has been recognised in various climate agreements (see Section 1). The finding here, revealed previously by only a few studies (e.g., Weilger & Sanubi, 2019), thus enriches the existing empirical literature by enabling a firmer conclusion that climate funding allocations during the 2000–2018 period were not unjust. In other words, even if we may not call this finding an example of distributive justice we may safely say that it does not indicate injustice either.

A unique revelation of this study is the non-linear, parabolic effect of vulnerability on all three types of funding. It enriches the current empirical knowledge in three major ways. Firstly, it further invalidates any concern about donors' proclivity towards allocating more mitigation than adaptation funding to climate vulnerable countries by revealing that the 'most vulnerable' countries were likely to receive considerably less mitigation funding than the 'least vulnerable' (Fig. 4). Secondly, the observed non-linear effects on adaptation and overlap fundings provide even further evidence of distributive justice in terms of allocating more funding to those that are 'particularly vulnerable' (Ciplet et al., 2013; Grasso, 2010; Khan et al., 2020; UN, 1992). This is because, as revealed, despite diminishing effects of vulnerability after certain thresholds, the 'most vulnerable' countries were still likely to receive more adaptation and overlap fundings than the 'least vulnerable' (Fig. 4). Although the term 'particularly vulnerable' lacks a consensus-based operational definition, either in the UNFCCC or successive climate agreements (Khan et al., 2020), common sense would dictate that countries having the highest vulnerability scores should fall within this category.

Thirdly and at the same time, however, the findings caution against complacency by revealing that the 'moderately vulnerable' were likely to receive more funding than the 'most vulnerable'. Although for mitigation funding, this observation was not a reason for concern, for adaptation and overlap fundings, this was not in complete harmony with distributive justice. Looking at the country-wise mean vulnerability scores (Appendix C) and the very low within-country variations in vulnerability over time (Appendix A), it appears that those most vulnerable countries were DR Congo, Solomon Islands, Mali, Liberia, Sudan, Chad, Guinea-Bissau, Micronesia, Niger, and Somalia. These SIDS and sub-Saharan African (SSA) countries are some of the world's most underdeveloped countries, affected not only by increased climatic extremes, but also by widespread poverty and food insecurities. Most of the SSA countries are also affected by prolonged and violent conflicts. This study thus substantiates, albeit partially, the prevailing concern regarding lower adaptation funding allocation for the world's 'most vulnerable' countries (Khan et al., 2020; Mott McDonald et al., 2021). It also suggests that, for climate financing to be just, this trend needs to be reversed. Evidence from previous studies (Betzold & Weiler 2017; Chen et al., 2018; Mori et al., 2019; Robinson & Dornan 2017; Weiler & Sanubi, 2019; Weiler & Klock, 2021), which report vulnerability's positive effects on adaptation funding allocation without considering its non-linear effects, were therefore partial.

The findings also raise an interesting question for debate. As shown in Fig. 4, some moderately vulnerable countries received higher mitigation funding than the least vulnerable countries, but those countries also received higher amounts of adaptation and overlap fundings than the least vulnerable. As discussed in Section 2, this may have happened because, for the donors, those countries (see examples like Vietnam, India, Nigeria, Angola, Congo, Cambodia, etc., in Appendix C) offered greater potential for both emission and vulnerability reduction. The observed significant negative effect of emissions per capita on mitigation funding provides further support in this regard, suggesting that this funding is perhaps not driven entirely by an emission reduction goal, but by a combination of both emission and vulnerability reduction goals. Whether such an approach conforms to distributive justice remains an open debate.

Findings regarding the control variables, although of secondary interest in this study, provide additional and complementary insights. Of particular importance is the finding that significantly less adaptation and overlap funds went to South Asia (SA) and Sub-Saharan Africa (SSA) (Table 2). This finding is concerning as these are two of the world's most climate-vulnerable regions (significant correlation coefficients $r = 0.187$ and $r = 0.577$ between vulnerability and SA and SSA regions, respectively, see Appendix B). In this regard, previous studies provided contradictory evidence – some reporting non-significant effects (Betzold & Weiler, 2017; Robinson & Dornan 2017) whilst others (Weiler et al., 2018; Weiler & Klock 2021) reporting significant positive effects – of the Africa region status on adaptation funding allocation. This contradiction arises probably because those studies considered 'Africa' as one region. As this study shows, the actual effect is negative when more specific regions are considered. This has important implications for allocation-based justice. All regions in Africa are not equally vulnerable from a socio-economic vulnerability perspective. North African countries, for example, are wealthier (hence less vulnerable) than most SSA countries. Allocation-based justice would then demand more emphasis on the latter group.

The significant positive effect of population on both adaptation and overlap fundings also appears important and matches very well with previous studies (Betzold & Weiler, 2017; Weiler et al., 2018). This may potentially be another concern from a justice viewpoint, since many highly vulnerable countries, especially the SIDS, are sparsely populated and small economies (Robinson, 2018; Scandurra et al., 2018). Population does not appear to be positively correlated with vulnerability either ($r = -0.041$, $p < 0.05$, see Appendix B), questioning its suitability as a criterion in adaptation funding allocation.

This study joins an overwhelming number of previous studies in confirming the significant positive effect of 'readiness' on the allocation of both adaptation funding (Bagchi et al., 2016; Betzold & Weiler, 2017; Chen et al., 2018; Mori et al., 2019; Robertsen et al., 2015; Robinson & Dornan 2017; Weiler et al., 2018; Weiler & Sanubi, 2019; Weiler & Klock, 2021), and mitigation funding (Bagchi et al., 2016; Halimanjaya, 2016; Weiler et al., 2019). The positive effect of readiness on mitigation funding is understandable, given that rational donors would be willing to invest more in countries providing maximum mitigation potential (Bagchi et al., 2016). Readiness can be a crucial indicator of such high-potential countries, who tend to have higher industrialisation, manifested in higher GDP (see the significant correlation $r = 0.573$ between readiness and GDP per capita in Appendix B). However, the same effect on adaptation and overlap funding can be concerning for distributive justice. As explained in Section 2, more vulnerable countries are expected to have less readiness, which was confirmed in this study ($r = -0.542$, Appendix B). This creates a paradox. Apart from a failure of vulnerable countries to present their funding proposals convincingly to donors (Chase et al., 2020; Fiala et al., 2019), weak readiness may raise legitimate concerns about their ability to successfully implement and manage climate-related interventions (Doshi & Garschagen, 2020). However, from a distributive justice viewpoint, these are the countries that may require more funding support to overcome adverse effects of climatic changes. This suggests the importance of embedding beneficiary capacity building support within global climate funds, e.g., as practised by the Adaptation Fund and the Green Climate Fund (Adaptation Fund, 2021; GCF, 2020c).

Evidence of donor self-interest found in this study have important implications. The observed significant effect of import on mitigation funding may be linked to the transfer of clean or emission reduction technologies (Burnham et al., 2013), but the same effect on adaptation funding is somewhat surprising as this funding is meant to be for vulnerability reduction. This perhaps manifests the conviction within multilateral institutions that "trade can play an important role in addressing the vulnerability of the poor to climate change" (World Bank Group & World Trade Organization, 2015, p. 54). Whether such an approach conforms to justice is difficult to establish without knowing the specific commodities imported by recipients for reducing their climatic vulnerabilities. Further studies could look into this.

The positive effect of ODA per capita corroborates the finding of Weiler et al. (2018) and suggests that donors probably combine or package climate-related aids with conventional development aids to achieve broader developmental outcomes. It, however, calls into question the so called 'additionality' of climate finance, which has been of long-standing concern amongst recipients. India, for example, refuted OECD's claim of providing $62 billion climate finance in 2014 and made a counter-claim that only $2.2 billion of the amount was "credible new and additional climate support" (Khan et al., 2020, p.261). A recent study also provides weak evidence of additionality in climate finance allocation (Weiler & Sanubi, 2019).

The application of a 'dynamic' modelling approach combined with an advanced GMM-based instrumental variable method provides more confidence in this study's findings. Such a methodological approach generated one of this study's unique and most significant insights – past funding significantly affects current funding. It also confirmed that the effects of vulnerability were long-lasting or persistent. The observed dynamic nature of climate financing coupled with the 'persistent' and 'non-linear' effect of vulnerability, and the positive effect of readiness, are perhaps indicative of what may be defined as a Low Funding Trap (LFT) for the world's most vulnerable countries. In this trap, lower readiness may lead to lower funding, which in turn, may lead to increased vulnerability and successive cycles of lower funding. The existence of such LFT is not good news and implies that, although positive developments have occurred since the 2015 Paris Agreement, more remains to be done to achieve distributive justice in global climate finance.

This study shows that determining the effect of vulnerability on funding allocation may be challenged by data and methodological limitations. Besides the well-known concern regarding the quality of donor-provided climate finance data (Khan et al., 2020; Robets & Weikmans, 2017), a lack of coordination between various data sources is another problem. For example, the ND-GAIN's vulnerability index had non-imputable missing data (for the entire 2000–2018 period) for 15 of the climate finance recipient countries listed on the OECD-DAC database (see Section 3.1). Consequently, the total number of observations included in statistical analyses from the merged dataset declined due to list-wise deletions, resulting in reduced confidence in some findings. An example is the case of the SIDS, nine of which had missing vulnerability data. Although the data from the rest 27 SIDS (75% of the fund-recipient SIDS) over 19 years constituted an acceptable sample size (27 X 19 = 513 observations), and the observed non-significant effect of the SIDS status variable matched with some previous studies (Betzold & Weiler, 2017; Mori et al., 2019), one might still wonder if the finding would have been different if data from all the 36 SIDS were available and analysed.

Moreover, it has long been recognised that operationalising the term 'particularly vulnerable' in climate funding allocation is challenged by the multiplicity of national level vulnerability assessment methods (Ciplet et al., 2013). The challenge remains as successive studies continue using different methods, e.g., the ND-GAIN vulnerability index, Structural Vulnerability to Climate Change Index (SVCCI), and Climate Risk Index (CRI) (Mori et al., 2019; Weiler et al., 2018). Underpinned by the IPCC's definition of vulnerability (IPCC 2007, 2014), the NDGAIN's vulnerability index used in this study seems to provide a realistic picture. It would be counter-intuitive to think that countries like DR Congo, Solomon Islands, Mali, Liberia, Sudan, Chad, Guinea-Bissau, Micronesia, Niger, and Somalia are not 'particularly vulnerable' as their socio-economic and political weaknesses are well-known. A method that discounts the social dimensions of vulnerability and equates vulnerability to climate change 'exposure' only (e.g., as in Betzold & Weiler, 2017; Robertsen et al., 2015; Weiler et al., 2018; Weiler & Sanubi, 2019) may not find these countries as particularly vulnerable. As discussed in Section 2, such an approach may not be tenable. For global climate finance allocation to be more just and transparent, an integrated global database, holistic vulnerability indicators combining both social and climatic dimensions, and a coordinated methodological approach to vulnerability assessment, would be required.

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Declaration of Competing Interest

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

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Appendix A. Supplementary data

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