Determinants of International Climate Finance: A Gravity Panel Model Approach

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Determinants of International Climate Finance: A Gravity Panel Model Approach

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Abstract

This paper addresses climate change by examining the determinants of international climate finance. In response to the effects and potential damages of climate change, countries and international institutions are increasingly making efforts to mitigate its impacts. While financial assistance are being increasingly mobilized to help countries confront this threat, many nations remain underprepared for the effects of climate change and are at risk of experiencing significant economic and social damage due to climate-related events. This paper focuses on the allocation of international climate finance, exploring the extent to which countries are supported in their climate change adaptation efforts, particularly with regard to more vulnerable nations. By employing a Gravity Panel Model that includes 140 recipient and 30 provider countries over the period 2000-2021, this paper shows that vulnerable countries to climate change are not likely to receive climate finance in the form of either grants or loans. Political ties and economic interests appear to play a significant role in the allocation of international climate finance.

JEL Classification Numbers: Q54, F35, C01

Keywords: international climate finance, climate vulnerability, gravity panel model

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1 Introduction

Which countries receive more international climate finance? Do vulnerable nations receive more international climate finance? What are the characteristics of countries that receive more international climate finance? What factors determine its allocation? Do the interests of donor countries play a key role in the flow of this finance ?

Over the past two decades, governments, international institutions and researchers have placed particular emphasis on the effects of climate change (IPCC, 2014). Climate change is expected to impact fundamental aspects of people's life around the world through natural disasters such as droughts, floods, sea level rise, storms or extreme temperatures. The potential effects of climate change on human, economic and natural systems are extensive, including ecosystem degradation, destruction of infrastructures and human habitat, famine, migration from rural areas, conflicts over arable lands, high urban concentration, food insecurity, effects on business production, reduced economic growth, declining of incomes and increased poverty (IPCC, 2021; Dunne et al., 2020; Diffenbaugh and Burke, 2019; Dai, 2013; Diffenbaugh and Field, 2013; Stern, 2007). Given the urgent need for action to address climate change across countries and to assist nations in building resilient economies and fostering greener growth, developed countries have been providing financial assistance to several nations since the 2000s. Following the 15th Conference of Parties (COP 15) of the United Nations Framework Convention on Climate Change (UNFCCC) in Copenhagen in 2009, this financial support significantly increased, with a commitment to mobilize USD 100 billion annually by 2020 for climate action in more vulnerable countries (UNFCCC, 2009). This goal was reiterated and extended to 2025 during the 21th Conference of Parties (UNFCCC, 2015).

The importance of climate finance is underscored by its critical role in the global response to climate change. It is expected to help countries cope with the effects of climate change and enhance their adaptation capacity by foster investments in climate-resilient infrastructures, research and development, renewable energy and human habitat, as well as by reducing income inequality to avoid exacerbating poverty, which can increase population sensitivity. Given the pivotal role of climate finance in addressing climate change and following the Copenhagen summit in 2009, research has increasingly focused on international climate finance and sought to explore its determinants (Barrett, 2014; Doku et al., 2021; Bayramoglu et al., 2023). Some studies have highlighted some similar determinants, such as the income level of recipients countries or colonial ties, but ambiguous responses still remain regarding whether more vulnerable or less vulnerable countries receive a greater share of climate finance. In this context, Barrett, 2014 argued that climate finance is not directed towards vulnerable areas, whereas Bayramoglu et al., 2023 argued that international climate finance is indeed targeted toward vulnerable countries.

To better understand the characteristics of countries that receive more climate finance and to address this ambiguous issue, this paper focuses on the allocation of international climate finance by investigating empirically its potential determinants using a Gravity Panel Model. This paper contributes to the literature on the international climate finance in three key ways. First, it applies a gravity model, commonly used in trade studies, to climate finance flows which has been less frequently used in previous studies. Second, it uses a large panel of countries, which allows for a more stable and generalized estimation of the results. Finally, it employs disaggregated climate finance data, distinguishing between grants and loans which may provide more detailed insights compared to previous studies. The main finding of this work is that vulnerable countries are not likely to receive international climate finance, either in the form of grants or loans, with economic interests and political ties playing a significant role in the provision of climate aid. The paper is organized as follows: The second section provides a summary review of potential determinants of climate finance, highlighting the needs of recipient countries and the self-interests of donor countries. Section 3 presents stylized facts related to climate finance allocation, while section 4 outlines the econometric framework. The last section discusses the conclusion and policy implications.

2 Potential Determinants of International Climate Finance

The provision of aid is generally explained as being altruistic in nature, but the self-interests of donors and the characteristics of recipients can influence the effectiveness of the aid provided (Alesina and Dollar, 2000; Berthelemy and Tichit, 2004; Younas, 2008). By analogy, it is reasonable to expect that the allocation of international climate finance follows a similar pattern to that of development aid. Therefore, the following subsections discuss the potential determinants of international climate finance, drawing from the development aid literature, which emphasizes both the needs of recipient countries and the interests of donor countries.

2.1 Recipient Countries View: Needs and Merits

Previous studies on the allocation of development aid suggest that donor countries take into account the needs of recipient nations, often providing more financial assistance to less developed countries (Alesina and Dollar, 2000). These countries typically lack the economic and financial resources needed to address social, economic, or environmental challenges. Providing assistance to these nations can help strengthen their economic and financial capacities. Population size is also highlighted as a factor in the allocation of development aid (Trumbull and Wall, 1994;

Tezano Vasquez, 200 8). An increase in population can heighten a country's needs in areas suchs as housing, food, energy, education (including human capital development and research), and healthcare. In this study, which focuses on climate aid allocation, another characteristic relevant to recipient countries is considered: climate vulnerability. This characteristic is identified as a key factor in determining which countries receive climate aid (Robertsen et al., 2015, Barrett, 2014). Climate change vulnerability, in the context of climate finance, serves as an equivalent to poverty in the literature on development aid. Given the varied impacts and potential damages of climate change, vulnerable countries are likely to suffer more severely, facing issues such as the destruction of housing, famine, economic losses, reduced production, rural migration, urban concentration, and land conflicts. Therefore, providing financial assistance to vulnerable countries can help them improve their adaptation capacity and manage the effects of climate change. Another important determinant of aid is the quality of a country's economic and political institutions. Countries with strong political and economic institutions are expected to use financial assistance more effectively to achieve the intended objectives (Doku et al., 2015; Persson and Remling, 2014).

2.2 Provider Countries View: Self interests and economic wealth

The interests of donor countries are also expected to influence aid allocation. Balla and Reinhard (2008) argue that recipients with strong political alignment with donor countries are more likely to receive increased development aid. Economic relationships such as trade partnerships, can also affect aid distribution, with recipient countries that import a significant amount of goods from donor countries receiving more aid (Berthelemy and Tichit, 2004; Younas, 2008). Hicks et al. (2010) suggest that donor countries might use environmental aid as a tool for export promotion. Similarly, Robinson and Dornan (2017) and Weiler et al.(2018) find a link between higher trade volumes and the allocation of development aid, indicating that aid may be used to strengthen trade ties with recipient countries. Alesinar and Dollar (2000) also contend that bilateral aid patterns are shaped by political and strategic considerations, such as colonial history and voting behavior in the United Nations, and that donor countries vary significantly in their levels of altruism. They argue that a former colony that maintains friendly political relations with its former colonizer is more likely to receive greater aid compared to another country with a similar poverty level. Collier and Dollar (2002) further assert that aid allocation is often inefficient from a poverty-reduction perspective. The economic wealth of donor countries also tends to influence the provision of aid in general and climate assistance in particular. Wealthier countries are more likely to provide climate finance. Fuchs et al. (2014) find that aid budgets generally increase as the wealth of donor countries rises. Higher income levels in donor countries make aid allocation more feasible and easier to implement. In line with this, faini (2006) argues that development aid tends to decrease with rising public debt, declining economic growth, and larger fiscal deficits in donor countries.

2.3 Previous studies on the determinants of Climate Finance

Following the Copenhagen summit in 2009, research has increasingly focused on tracking climate finance and exploring the factors that determine its allocation. Several studies have sought to define the motivations behind the provision of climate finance. Regarding donors characteristics, Fuchs et al. (2014) argued that climate aid is positively correlated with the wealth of donor countries. On the other hand, with respect to recipient needs, Barrett (2014) found that climate vulnerability is not a determining factor in receiving climate finance in Malawi and that climate finance tends to go to regions with higher income levels, which appear equipped to use the funding efficiently. Halimanjaya (2015) showed that developing countries with lower GDP per capita, higher CO_2 intensity and good governance are more likely to be selected as recipients of climate mitigation finance. Using ordinary least squares and the 4P framework for Sub-Saharan African countries from 2010 to 2013 and focusing on seven donors (Canada, France, Japan, United Kingdom, Netherlands, Germany and Sweden), Robertsen et al. (2015) found that climate vulnerability, measured by the exposure component of the ND-GAIN index is positively but not significantly associated with climate finance for adaptation. They identified political regime (Polity 2), language and development aid as positively and significantly affecting the provision of climate adaptation finance. Weiler et al. (2018), using a two stage Cragg's model over the period 2010-2015, argued that trade ties, as measured by donors exports to recipient countries, drive adaptation aid. They also found that vulnerable countries, as measured by the exposure component of ND-GAIN Vulnerability index and the Climate Risk Index of Germanwatch tend to receive more adaptation aid. Additionally, they reported that colonial ties, development aid and population are positively and significantly associated with adaptation aid. Similarly, Weiler and Sanubi (2019), applying the same model and focusing on African countries from 2010-2016, argued that governance framework of recipients, as measured by worldwide governance indicators, and colonial ties are positively and significantly linked to both climate adaptation finance and climate mitigation finance. They also found that climate vulnerability, measured by the ND-GAIN exposure component, is positively and significantly associated with climate adaptation finance, albeit only at the 10 percent confidence level. Regarding Sub-Saharan African countries and using a Generalized Method of Moments (GMM), Doku et al. (2021) analyzed a panel of 43 countries over the period 2006-2017, finding that countries with stronger rule of law, higher population growth rates, higher poverty levels, better ease of doing business, deeper social inequality, and better ICT usage attracted more climate finance. In a more recent study using IV-2SLS estimation on bilateral climate aid from 2002 to 2017, Bayramoglu et al. (2023) found that donor exports, recipient population size, colonial ties, geographical proximity (measured by the distance between the capitals of donor and recipient countries), and donor GDP are positively and significantly associated with climate aid. They also argued that vulnerable countries, as measured by the ND-GAIN Vulnerability index, are likely to receive climate aid.

Most of theses previous studies focused on aggregated and unilateral climate finance data and small sample of countries. In our study, we focus on bilateral data and extend the analysis to a large sample of countries over a longer period (2000 to 2021). Moreover, compared to previous studies, particularly Bayramoglu et al. (2023), we use a climate vulnerability indicator that is less correlated with economic conditions of recipient countries, which allows for less biased results. The higher correlation of the ND-GAIN Vulnerability index (used in their paper) with the economic conditions of recipients countries [1] might explain the positive and significant association between Climate aid and vulnerability, as most recipient countries are developing nations with lower GDP per capita, and are therefore automatically and hierarchically classified by the ND-GAIN indicator as more vulnerable to climate change. Another contribution of this paper to the literature on climate aid determinants is our disaggregation of climate finance into grants and loans, which provides more detailed information than aggregated data.

3 International Climate Finance

Financial assistance is a key ingredient of the global response to climate change. The climate resilient-development of countries depends on the amount of funding available to support their efforts. Climate finance is seen as a tool to help vulnerable countries cope with the effects of climate change and climate related-risks through disaster prevention, preparedness, and capacity building (OECD, 2011). The United Nations Framework Convention on Climate Change (UNFCCC) defines Climate finance as "local, national or transnational financing drawn from public, private and alternative sources of funding that aims to support adaptation and mitigation actions to address climate change". Climate finance flows are typically categorized into national climate finance (financing within a country from public or private sources) and international climate finance, which includes bilateral and multilateral climate finance. Bilateral climate finance refers to financial assistance provided by one country to another, while multilateral climate finance involves funding from international institutions to a country. In this study, we focus exclusively on bilateral climate finance.

[1] In sub-section 4.1.2 and Appendix B, we show that the ND-GAIN Vulnerability indicator is highly correlated with a country's GDP per capita. Additionally, the correlation between the ND-GAIN Vulnerability index and economic variables is also noted by Kling et al. (2021).

3.1 General view

Data on climate finance were sourced from the OECD DAC statistics database. The initial dataset includes information such as the year of provision, the type and specific name of the donor, the recipient countries, the amount of climate finance, and the type of financial instrument used (grant or debt instrument). The providers may be multilateral donors (such as the World Bank, regional development banks, or other international institutions), private donors, or DAC (Development Assistance Committee) and Non-DAC donors, which correspond to donor countries. For this study, we focused on DAC and Non-DAC donors, representing donor countries, specifically examining bilateral climate finance (from a donor country to a recipient country). We created a new dataset by retaining only the DAC and Non-DAC donors, the year of provision, the amount of climate finance in 2021 USD thousand (referred to as "climate-related development finance" in the original database) and the type of financial instrument (grants or loans). Using coding techniques such as data combination and merging, we reconstructed a bilateral dataset that details donor countries, recipient countries, the total amount of climate finance allocated per year to each recipient by each donor country, and the breakdown of climate finance into grants and loans. The initial dataset comprised 36 donor countries and 154 recipient countries for the period 2000-2021. We excluded 6 donor countries (Azerbaijan, Estonia, Hungary, Latvia, Liechtenstein and Romania) because they provided climate finance only one to four times to one or a few recipients throughout the entire period. Additionally, we removed 3 recipients countries (Anguilla, Bahrain and Slovenia) due to insufficient observations (only one to three climate finance flows) and 11 other countries [2] due to the absence of observations for the Vulnerability indicator (CV03). The final dataset consists of 30 donor countries and 140 recipient countries.

A graphical analysis of bilateral climate finance trend reveals that following the Copenhagen summit (2009), bilateral climate finance nearly doubled in the year immediately after the summit and increased by approximately sixfold between 2009 and 2021 (Figure 1). As previously mentioned, we focus on bilateral climate finance (funds transferred from one country to another) to better understand both the needs of recipient countries and the motivations behind the allocation of these funds. We also distinguish between two type of financial instruments: grants and loans. Grants account for a smaller portion of bilateral climate finance (about 30 %), while loans make up around 70%. Additionally, the overall trend in total climate finance closely follows the trend in loans (Figure 1), indicating that loans are a critical component of international climate finance. Japan emerges as the largest provider, contributing around 42% of total bilateral climate finance, followed by Germany (24%), France (14%) and United States (4%). The six major donor coun-

[2]These countries include Cook Islands, Kiribati, Kosovo, Montserrat, Niue, Saint Helena, South Sudan, St. Vincent and the Grenadines, Tokelau, Tuvalu and Wallis and Futuna

tries (Japan, Germany, France, United States Norway and United Kingdom) collectively account for about 83% of total bilateral climate finance (Figure 2). Japan and France primarily offer their climate aid in the forms of loans (approximately 92% of Japan's climate aid and 94% of France's). These two countries, along with Germany, are the larger providers of loans, representing over 60% of the total climate finance from all providers (Figure 6). On the other hand, while their total climate aid is relatively small, United States, Norway and United Kingdom primarily provide their climate aid in form of grants (Figure 2). These three countries are among the top five grant providers, with Germany being the largest (Figure 4). Regarding recipient countries, India is the largest recipient, receiving around 17% of total bilateral climate finance, with about 93% of this aid in the form of loans (Figure 3). The five largest recipient countries are in Asia (India, Indonesia, Bangladesh, Philippines and Vietnam), and they are also the top recipients of loans (Figure 7). The largest African recipient is a North African country, Morocco, which receives about 4% of total bilateral climate finance. In the Americas, Brazil is the largest recipient, receiving about 3% of total bilateral climate finance (Figure 3). Most of the major recipient countries primarily receive climate aid in the form of loans, with the exception of Brazil and Kenya. Additionally, the countries that receive the most grants are predominantly in Africa and Asia (Figure 5).

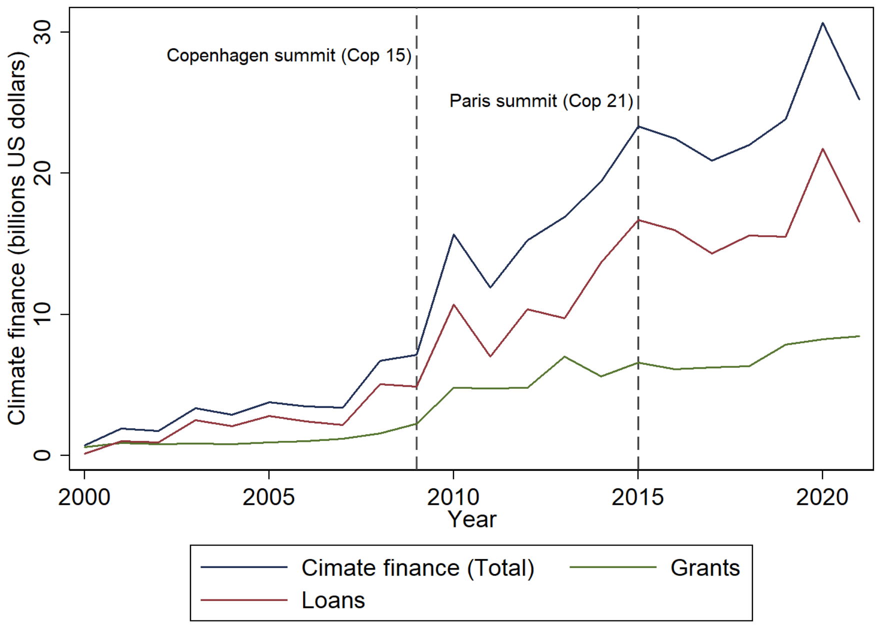

Figure 1: Evolution of Bilateral Climate Finance

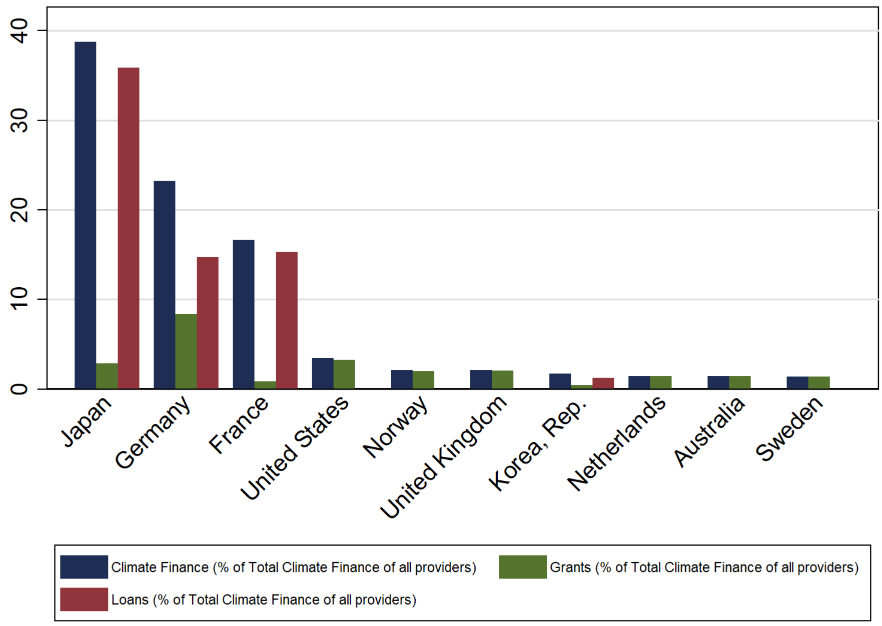

Figure 2: Most provider countries of Bilateral Climate finance (% of Total Climate Finance of all providers)

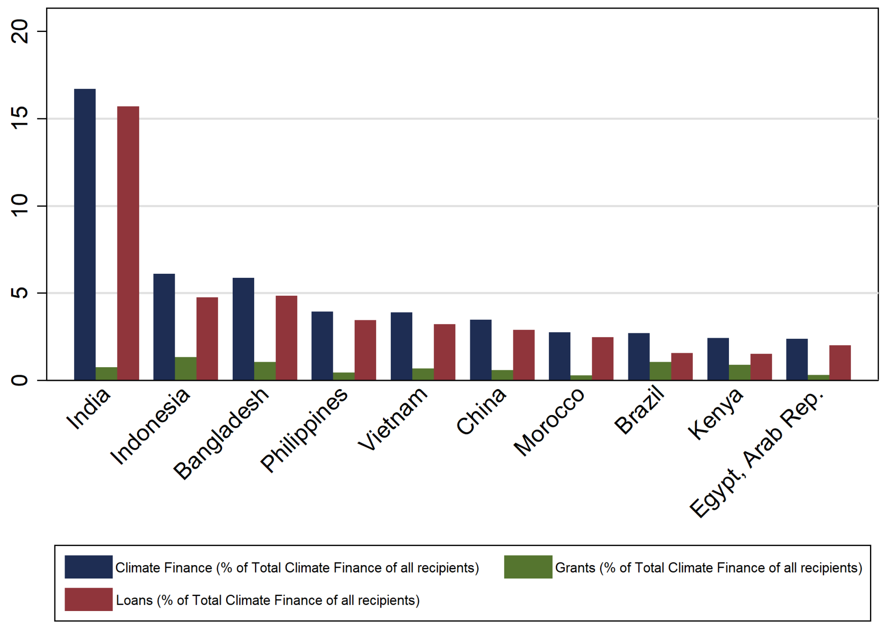

Figure 3: Most recipient countries of Bilateral Climate finance (% of Total Climate Finance of all recipients)

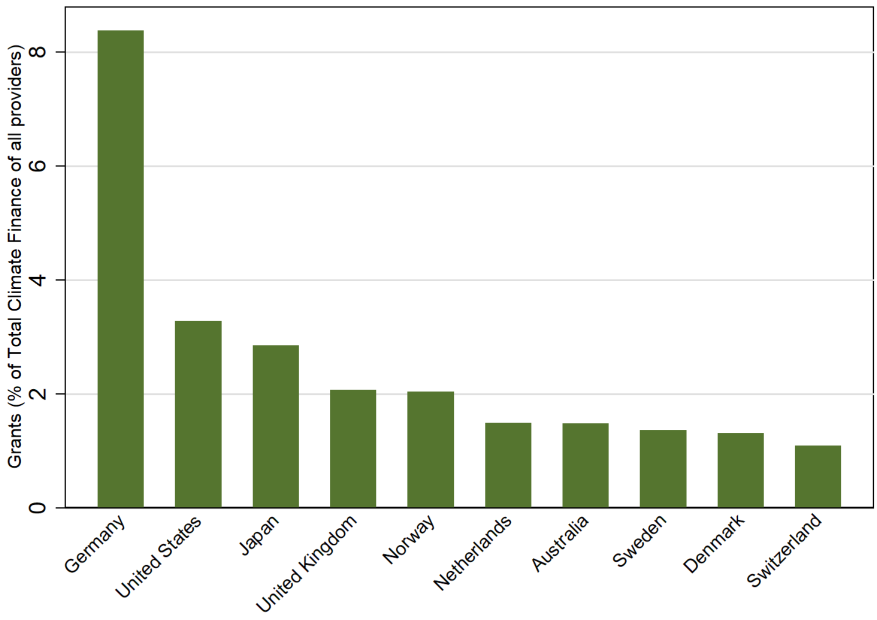

Figure 4: Most provider countries of Grants (% of Total Climate Finance of all providers)

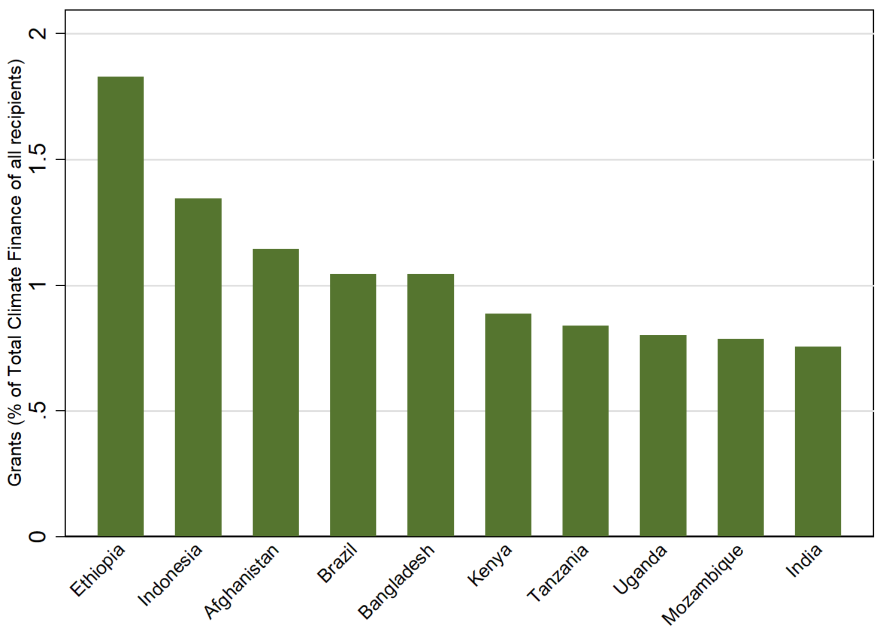

Figure 5: Most recipient countries of Grants (% of Total Climate Finance of all recipients)

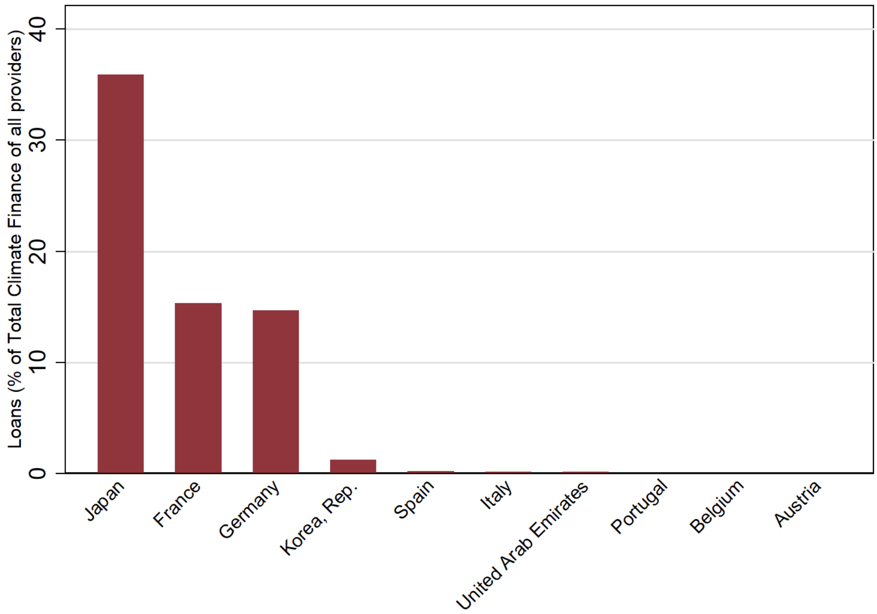

Figure 6: Most provider countries of Loans (% of Total Climate Finance of all providers)

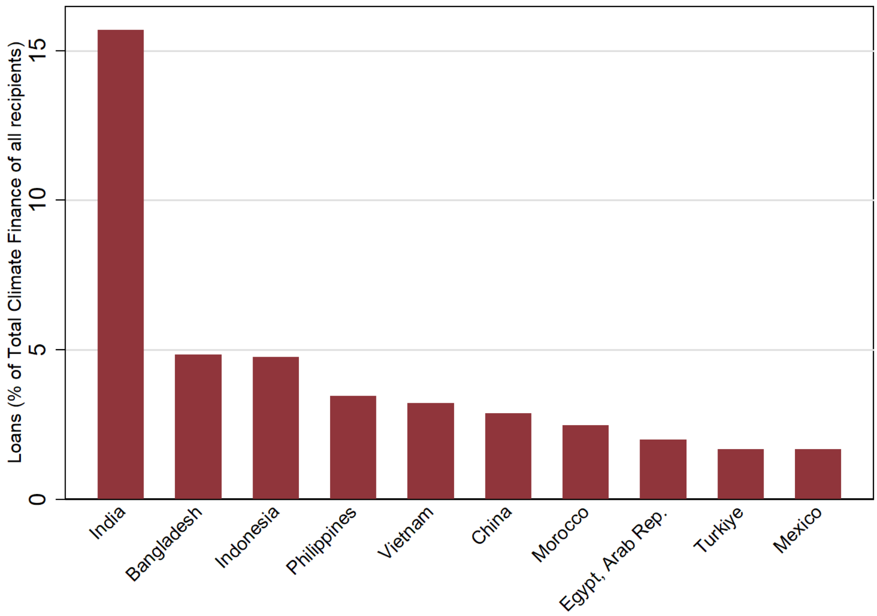

Figure 7: Most recipient countries of Loans (% of Total Climate Finance of all recipients)

3.2 Distribution by region of Recipient countries

This section provides an additional overview of bilateral climate finance by comparing the regions of Africa, the Americas, Asia, Europe and Oceania. We analyze total international climate finance as well finance distributed in the form of grants and loans. Notably, Asian countries receive the largest share of international climate finance, accounting for about 56% of the total flows (Figure 9). This region also receives the majority of its climate aid in the form of loans, with approximately 79% of the aid provided as loans. African countries are the second-largest recipients of bilateral climate finance, receiving about 23% of the total climate finance. The African region is also the largest recipient of grants, with more than 60% of its aid provided as grants. In contrast, countries in Oceania, which are among the most vulnerable to climate change receive the smaller share of climate finance (less than 3% of the total) and predominantly in the form of grants. American and European countries receive less climate finance compared to Asia and Africa, and also receive a higher proportion of their climate aid in the form of loans rather than grants.

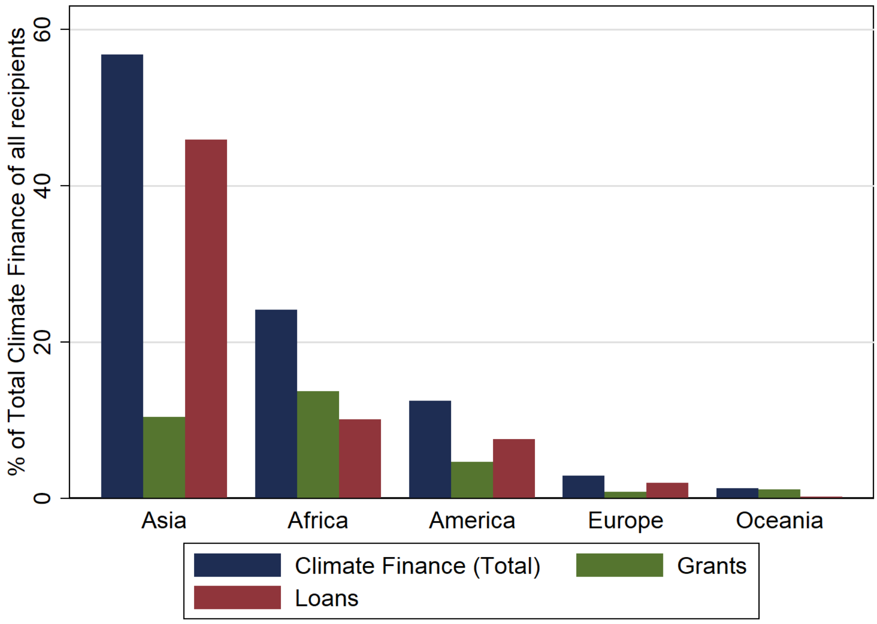

Figure 8: Climate Finance (Total), Grants and Loans by region (% of Total Climate Finance of all recipients)

3.3 Provider countries view

Figures 12 and 14 reveal that donor countries often direct climate finance to their former colonies. For example, Portugal allocates about 70% of its climate aid to its former colonies, such as Cabo Verde, Mozambique, Sao Tome and Principe, and Angola (Figure 12). Similarly, Spain directs around 50% of its climate aid to its former colonies, including Peru, Bolivia, Nicaragua, Colombia, Ecuador, and Guatemala (Figure 14). This indicates that colonial ties are likely to influence the distribution of climate finance. Donor countries also tend to support countries within the same region or continent. In other words, donor countries are inclined to assist their neighboring countries (e.g., Australia, Japan, New Zealand or Slovenia, see Figures 9,10,11 and 13). For instance, more than 70% of Japan's climate aid is directed towards Asian countries, over 60% of New Zealand's climate aid is allocated to Oceania, and more than 70% of Slovenia's climate aid is focused on European countries. This pattern supports the notion that geographical proximity may significantly influence the allocation of bilateral climate finance.

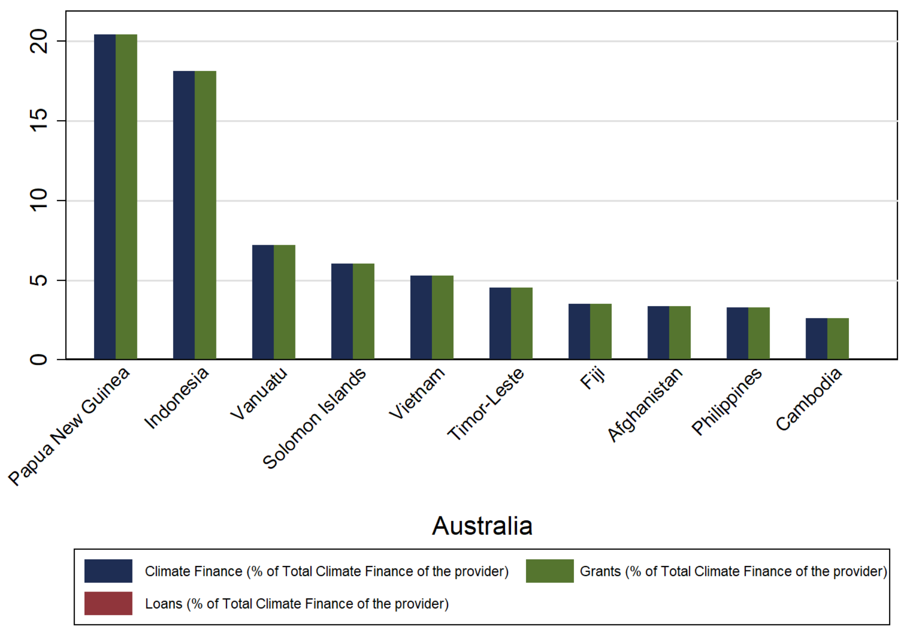

Figure 9: Australia and its most recipients (% of the Total Climate Finance of the provider)

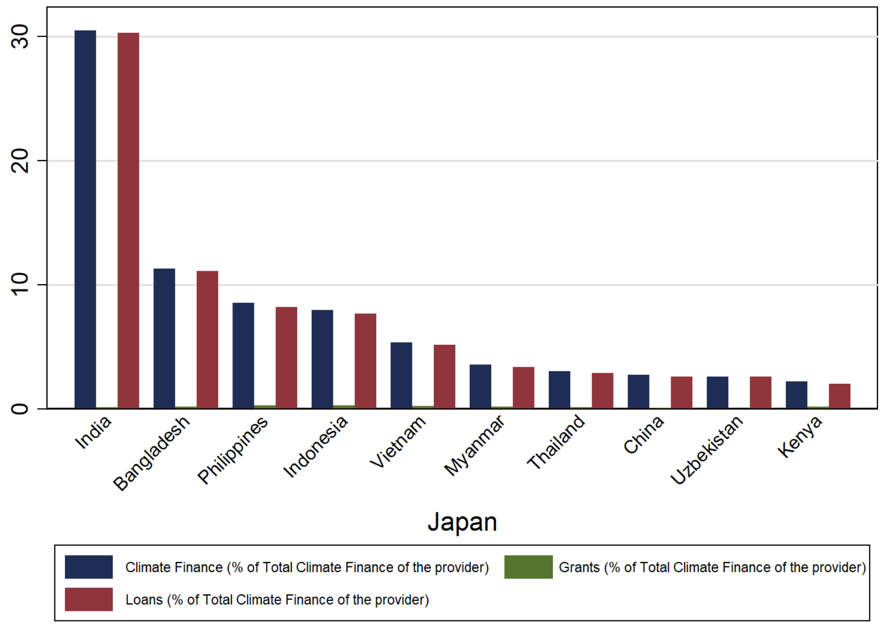

Figure 10: Japan and its most recipients (% of the Total Climate Finance of the provider)

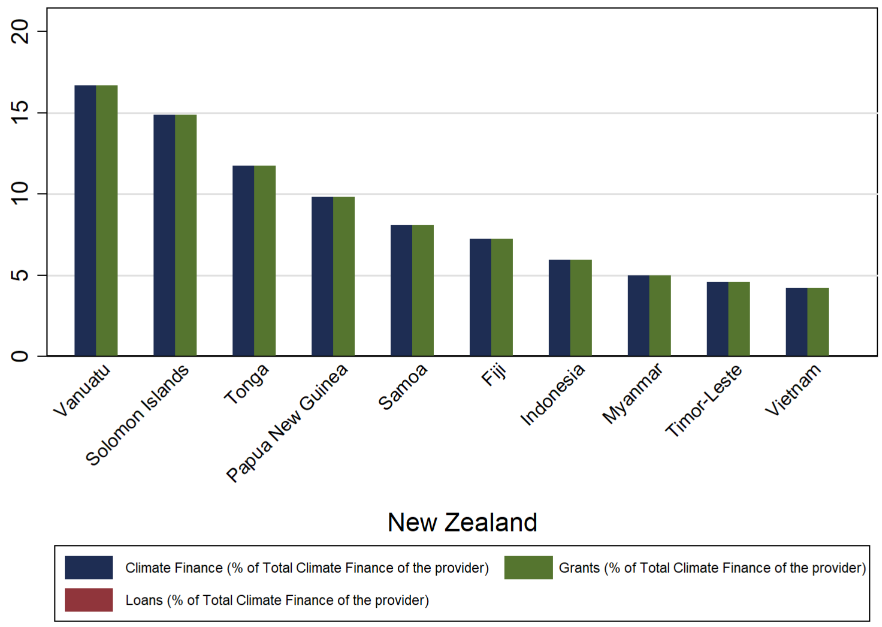

Figure 11: New Zealand and its most recipients (% of the Total Climate Finance of the provider)

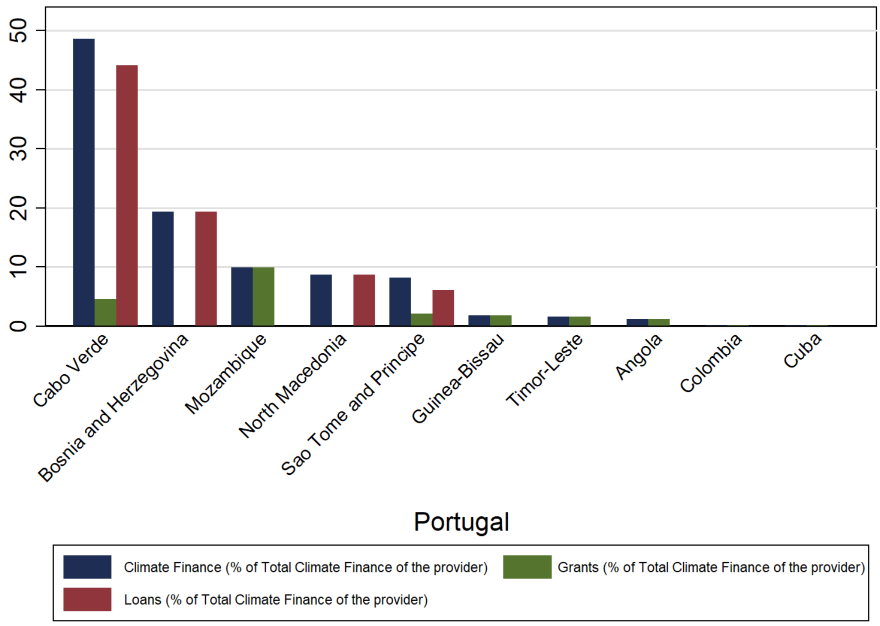

Figure 12: Portugal and its most recipients (% of the Total Climate Finance of the provider)

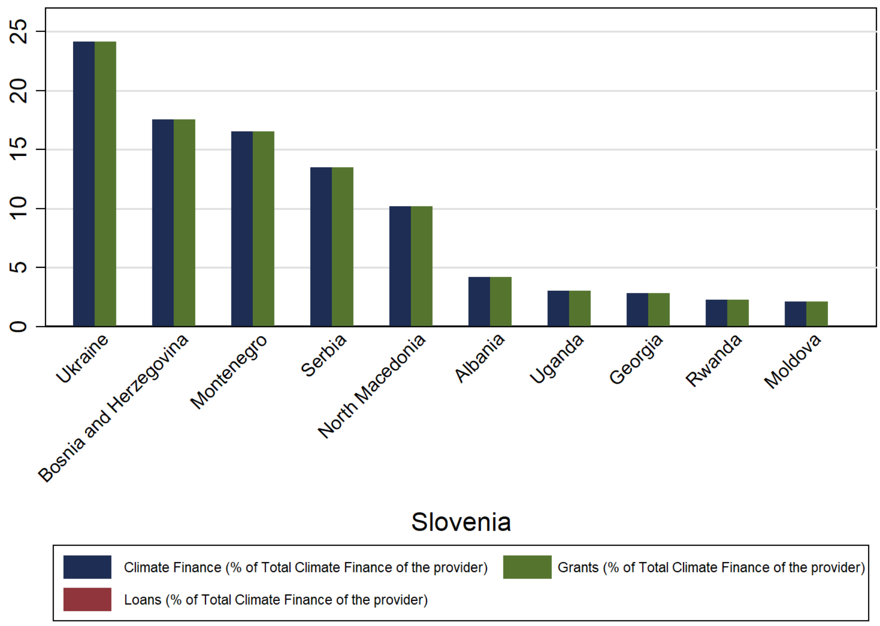

Figure 13: Slovenia and its most recipients (% of the Total Climate Finance of the provider)

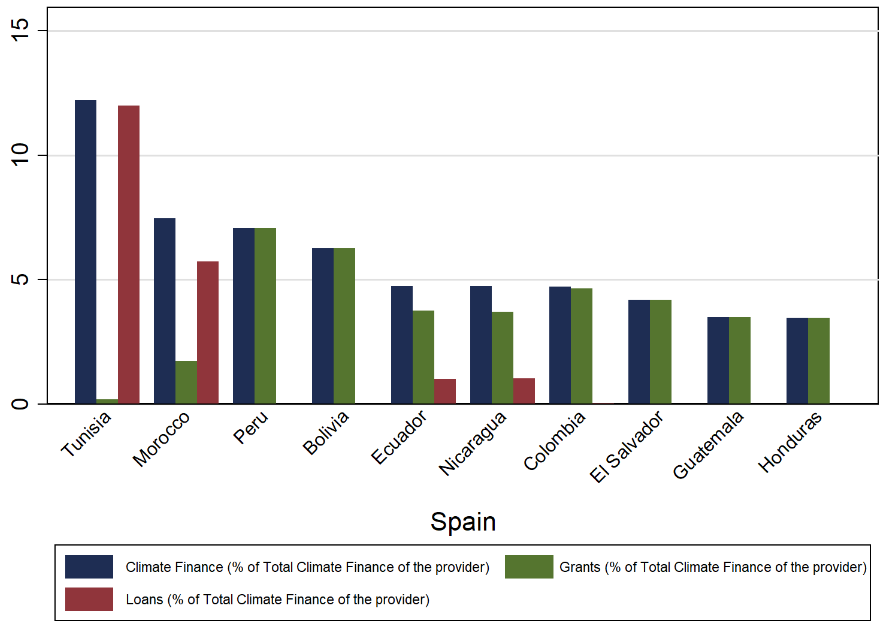

Figure 14: Spain and its most recipients (% of the Total Climate Finance of the provider)

Stylized facts indicate that African countries, many of which have low income levels, receive a higher proportion of grants compared to other regions. This suggest that grants are more likely to be allocated to countries with lower GDP per capita and, consequently, limited repayment capacity. Additionally, several donors countries tend to provide aid to their former colonies and countries with which they share geographical proximity. Thus, it can be inferred that both the GDP per capita of recipient countries and proximity factors may influence the flow of climate finance. The econometric analysis in the following section will test these hypotheses and identify other factors that may affect the allocation of climate aid.

4 Econometric Methodology

This section outlines the econometric framework regarding the potential determinants of international climate finance by estimating a gravity panel model using bilateral data, which includes information from both recipients and providers.

4.1 Data

The empirical analysis utilizes a sample of 140 recipient countries and 30 provider countries spanning the years 2000 to 2021. The data is sourced from various databases, including the OECD, CEPII and the World Bank′s Worldwide Development Indicators (WDI).

4.1.1 Dependent variable

The dependent variable is international climate finance as described in the previous section, referred to as “CFinance” and it is categorized into Grants and Loans in the econometric estimation.

4.1.2 Recipient variables

The model incorporates several independent variables, particularly those related to recipient characteristics, which are outlined as follows.

◦ Climate change Vulnerability (CV03).Climate change vulnerability is expected to be positively associated with international climate finance flows, as vulnerable countries require financial support to aid their climate change adaptation processes. In this study, we utilize a newly constructed indicator (CV03)[3] derived from the ND-GAIN Vulnerability indicator (see Appendix B). While the ND-GAIN Vulnerability indicator has been employed in several recent studies (Fuller, 2021; Halkos et al., 2020), it may present issues of biased results when employed in econometric models due to its strong association with the economic development of countries. The new indicator addresses theses biases in results and minimizes economic considerations in measuring climate vulnerability. The values of this indicator range from 0 to 1, where a value close to 1 indicates a high level of vulnerability to climate change.

◦ Gross domestic product per capita (GdpcR) at 2010 constant prices, from the World Bank. This variable allows to have an overview on the size of the economy and the level of development of the recipient countries. It is expected a negative association between high level of Gross

[3] The indicator CV03 is calculated using the arithmetic mean of the sub-indicators from the ND-GAIN Vulnerability indicator that exhibit a correlation with GDP per capita (Gross Domestic Product per capita) of less than 0.3 in absolute value. This threshold was chosen to ensure that at least one sub-indicator is retained for each of the six life sectors: Food, Water, Health, Ecosystems, Habitat, and Infrastructure. As robustness check, we developed others indicators with the thresholds of 0.4 (CV04) and 0.2 (CV02) in absolute value, but the indicator CV03 remains the best indicator since there is no significant relationship between CV03 and GDP per capita and temperature significantly affects CV03, which aligns with trends of global warming. This new indicator shows a lower correlation with the GDP per capita of recipients countries compared to the ND-GAIN Vulnerability indicator (see Appendix B).

Domestic Product per capita and climate finance assistance, as provider countries tend to prioritize less developed countries (Robertsen et al., 2015; Neumayer, 2003).

◦ Natural resource rent (Nrent). This variable is used as an indicator of natural resource wealth, encompassing oil, natural gas, and minerals, and is utilized to characterized resource-rich countries [4] within the model. Indeed, these resource-rich nations appear to be among the most vulnerable to climate change. Despite their abundant resources, they encounter numerous economic and social challenges, including social and political conflicts, corruption, unemployment and high poverty levels (Beck and Poelhekke, 2017; Sachs and Warner, 2001; Sala-i-Martin and Subramanian, 2003). Additionally, they face the pressing need to diversify their economies, witch could result in a reduction of natural resource production and, consequently, a decline of income. These countries require support and assistance to ensure their economic development and adaptation to climate change. The purpose of employing this variable is to investigate whether resource-rich countries are more likely to attract increased climate finance flows, given their unique circumstances. These countries also face the challenge of the implementation of climate-friendly policies aimed at reducing greenhouse gas emissions from natural resource extraction, which contribute to global warming and exacerbates local environment degradation (Afolabi, 2023; Agboola et al., 2021), thereby increasing their vulnerability to climate change. In the robustness check, we focus exclusively on a sample of resource-rich countries. Data for this variable is available for a wide range of countries and has also been used in previous studies (Bhattacharyya, 2014; Beck and Poelhekke, 2017). The data is sourced from the World Bank database.

◦ Population (Pop). This variable helps to assess the size of a country. It is expected a positive association between population and international climate finance flows (Trumbull and wall, 1994; Tezanos Vasquez, 2008). An increase in population can raise the needs of countries in terms of housing construction, food supply, and energy provision. The data is sourced from the Word Bank database.

◦ Institutional Quality (IQ). The Institutional Quality indicator assesses the level of governance and is derived from Worldwide Governance Indicators through Principal Component Analysis (PCA). These indicators include Voice and Accountability, Political Stability and Absence of Violence and Terrorism, Government Effectiveness, Regulatory Quality, Rule of Law and Control of Corruption. As a variable related to recipient merit, institutional quality is expected to influence the allocation of development aid (Clist, 2011; Michaelowa and Michaelowa, 2012), and in the same manner the allocation of climate aid. Countries with high levels of institutional quality are expected to manage financial assistance effectively in the implementation of climate policies. The indicator's value has been normalized on a scale from 0 to 1, where a value close to 1 indicates a

[4] The WBG (World Bank Group) Fragile , Conflict and Violence Group - Investment Climate Teams defines resources-rich countries as those where the average total natural resources rent (% of GDP) over the past three years is at least ten percent.

strong institutional framework.

○ Greenhouse Gas emissions per capita (GHGR). This variable pertains to the greenhouse gas (GHG) emissions of recipients countries. An increase in GHG emissions can lead to environmental degradation and contribute to Global warming. Therefore, climate finance is expected to be directed towards countries that generate higher levels of GHG emissions, in order to assist these nations in adopting climate-friendly policies. In this context, Halimanjaya (2015) noted that developing countries with higher CO_2 intensity tend to receive more climate mitigation finance. The data is sourced from EDGAR (Emissions database for Global Atmospheric Research).

4.1.3 Provider variables

In the model, we include variables related to provider countries that pertain to income levels (GdpcP) and the environmental data of donors.

○ Gross Domestic Product per Capita (GdpcP) at 2010 constant prices. Countries with higher greater financial resources are anticipated to offer more financial assistance to developing nations. The data is sourced from the World Bank database.

○ Greenhouse Gas emissions per capita (GHGP). This variable pertains to the GHG emissions of donor countries. The Cancun agreements of 2010 (COP 16) asserted that polluting countries should contribute to climate finance in accordance with their current and historical GHG emissions, which is based on the "Polluter pays" principle (Schalatek et al., 2012). Therefore, we can expect that donor countries with higher GHG emissions will be pressured to provide more climate finance. The data is obtained from EDGAR (Emissions database for Global Atmospheric Research).

4.1.4 Common variables

Other bilateral variables are also incorporated into the model, such as colonial ties (Colonial history), proximity variables (e.g., distance from capitals cities), and Bilateral Development Assistance flows (ODA). Several of these variables serve as indicators of donor interests.

○ Exports from provider to recipient countries (Exports). This variable can be regarded as a measure of the economic interests of provider nations. Indeed, countries with significant trade flows to recipient countries are expected to offer more financial assistance to their partners in order to strengthen their trade relationships. Therefore, a positive association between climate finance and exports is expected, as suggested by previous studies (Bayramoglu et al., 2023, Weiler et al., 2018). The data is sourced from the CEPII database. Since the data is in current US dollars, we adjusted the export values for inflation using the US Consumer Price Index (CPI) (base 2010) from the World Bank Development Indicators (WDI), following Bayramoglu et al. (2023).

◦ Colonial history (Col). Colonial history is anticipated to impact the allocation of international climate finance. Betlozt and Weiler (2016) assert that donor-recipient relationships matter and past colonial ties can influence the distribution of development aid to recipient countries. A positive association is expected between climate finance flows and an existing colonial history between provider and recipient countries. The data is also obtained from the CEPII database.

◦ Diplomatic Disagreement (DiploD). This variable pertains to the political distance between the provider country and the recipient country, derived from UN Assembly votes. A high value indicates a significant political divergence in voting patterns at the UN Assembly between the two countries. A positive coefficient for this variable suggests that the provider country may be seeking to gain political support from the recipient country in UN Assembly votes. Conversely, a negative coefficient implies that provider countries tend to allocate less climate finance to countries that do not align with their political stance. The data is sourced from CEPII.

◦ Trade Agreements (RTA). This is a dummy variable that indicates whether the provider and recipient countries have ratified treaties concerning bilateral trade. The data is also sourced from CEPII.

◦ Distance (Distcap). Countries that are geographically close are more likely to engage in bilateral relations, such as trade exchanges, political ties, agreements (e.g., countries in European Union), or financial assistance. In this work, we measure the distance in kilometers between the capitals of the provider and recipient countries. Data is obtained from CEPII.

◦ Official Development Assistance (ODA). Countries that already receive development assistance from a provider country are likely to obtain additional climate finance from that same provider. This can be viewed as an established aid network that reduces transaction costs for providers. Hoeffler and Outram (2011) argue that an existing aid relationship can attract new aid. The data comes from the World Bank database. Since the data is available separately for each provider country, we combined data from each provider to obtain a new dataset, and as it is presented in current US dollars, we have adjusted the ODA values for inflation using the US Consumer Price Index (CPI) (base 2010), following Bayramoglu et al. (2023).

◦ Bilateral Investment treaties (BIT). This variable relates to investment treaties between the provider and recipient countries during the specified period. The data is sourced from the Electronic Database of Investment Treaties (EDIT) provided by the World Trade Institute - University of Bern. The initial database involved a textual analysis of bilateral investment treaties among various countries, noting the year of signature, termination date, and partner countries. We created a new database with a dummy variable that takes the value of 1 if an investment treaty exists during the specified period and 0 if it does not or if the treaty has ended. This variable is expected to positively influence climate finance flows, as the provider country may use climate finance to foster investment relationships with the recipient country.

Variables	Mean	St.Dev	Min	Max	N
CFinance (millions USD)	3.0616	45.7894	0.0000	5568.024	92400
Grants (millions USD)	0.9505	6.6095	0.0000	448.645	92400
Loans (millions USD)	2.0774	44.3879	0.0000	5563.981	92400
CV03	0.3988	0.0718	0.2739	0.6142	92400
Exports (millions USD)	0.4167	4.3808	0.0000	265.0104	92400
GdpcP (USD)	40594.82	20822.97	6423.421	112417.9	92400
GdpcR (USD)	4451.767	4393.807	255.1003	22879.51	89370
Nrent (% of GDP)	8.4785	11.4991	0.0000	88.5923	89700
Pop (millions)	40.9901	156.4382	0.0102	1412.36	92400
IQ	0.4439	0.1481	0.0000	0.8568	90780
GHGP (tons CO2-eq)	13.3378	6.3637	5.2128	42.7517	92400
GHGR (tons CO2-eq)	5.2250	9.2188	0.4896	179.3064	89100
ODA (millions USD)	12.1436	82.7421	-1206.34	11227.79	92400
Col (dummy)	0.0302	0.1712	0	1	92400
DiploD	1.5223	0.6950	0.0001	4.8269	85848
RTA (dummy)	0.1751	0.3801	0	1	90930
Distcap (km)	7725.624	3877.382	117	19599	90930
BIT (dummy)	0.2179	0.4128	0	1	92400

Table 1: Summary Statistics

4.2 Model

Since, our focus is on bilateral data (i.e., financial flows from one country to another), the most suitable model is a Gravity Panel model. This model effectively incorporates both bilateral data and individual data from both donor and recipient countries. Gravity Models, inspired by Newton's theory of gravity are commonly used in international trade analysis.

4.2.1 Traditional framework of gravity model

The Gravity Model originates from Newton's Law of Universal Gravitation, proposed in 1687. According to Newton, any object in the globe attracts another object with a force proportional to the product of their masses and inversely proportional to the distance between them. Beyond the field of physics, gravity models were adapted to analyze trade between countries. The idea is that trade between countries is positively correlated with their economic size (level of development) and negatively correlated with the distance between them. Tinbergen (1962) is recognized as one of the pioneers in formulating an econometric version of the gravity model for empirical analysis. As a result, Tinbergen's gravity equation has become a foundational model in the study of international trade flows. The Gravity Model is advantageous because it incorporates both bilateral data and individual data from the countries involved, offering insights each country's characteristics and their mutual relationships. The basic equation of the traditional gravity model, which posits that trade between two countries (i and j) is positively related to their incomes and negatively related to the distance between them, is represented as follows:

$$X_{ij} = \alpha \frac{Y_i Y_j}{Dist_{ij}} \tag{1}$$

With α a constant, X_{ij} is related to the value of bilateral trade between country i and j, Y_i and Y_j are related to respective gross domestic product (GDP) of country i and country j and $Dist_{ij}$ is related to the bilateral distance between the two countries. The linear form of this equation is specified as follows:

$$lnX_{ij} = \beta_0 + \beta_1 lnY_i + \beta_2 lnY_j + \beta_3 lnDist_{ij} + \epsilon_{ij} \tag{2}$$

With ϵ_{ij} an error term.

Today, gravity models are used in various fields of studies, from international trade (Linnemann, 1996; Egger, 2002; Helpmann et al. 2008; Melitz, 2008; Milner and McGowan, 2013; Baltagi et al. (2015); Santana-Gallego et al. 2016) to migration (Docquier et al.2010), bilateral foreign investments (Chang, 2014; Pericoli et al. 2014; Egger, 2010) or foreign aid (Berthelemy and Tichit, 2004; Younas, 2008).

4.2.2 Estimation of gravity model

The econometric methods used to estimate gravity model are diverse. However, a common view is that the accuracy of regression estimates is significantly higher in panel data, primarily because of the larger sample size compared to cross-sectional or times-series studies. Cross-sectional investigations may encounter biased results and misleading conclusions due to potential issues with omitted variables and heterogeneity (Pesaran, 2015; Wooldridge, 2002). Gravity Model is estimated either in linear form or non-linear form. In the early days of gravity models, the linear form was used and models were estimated by considering the log-linear specification. The methods of estimation in this context was Ordinary Least Squared (OLS) or traditional Panel estimations (e.g., Panel fixed effects). As log linear OLS techniques was unable to include observations with zero values because the log of zero is undefined, most studies dropped observations with zero values, using only positive values for estimation. However, several issues can arise with these methods such as loss of information due to the removal of zero observation flows, sample selection bias, biased coefficients and heteroskedasticity issue by using logged values [5]. (Santos

[5]Heteroskedasticity arises when the variance of the error terms is correlated with the dependent variable. Hence, bigger values of the dependent variable tend to have higher variance errors

Silva and Tenreyro, 2006). Zero values flows are a problematic issue in gravity model in log-linear specification since the logarithm of zero is not defined. Alternative methods without suppressing all zero values in the dataset, such as Truncated and censoring methods (e.g., Panel Mean-Group) can also lead to biased estimation for the omission of data (Baldwing and Harrigan, 2011; Burger et al. 2009; Martin and Pham, 2015). Linders and de Groot, 2006 and Burger et al., 2009 agued that these methods, where the zero values are substituted by a small positive constant, are arbitrary without any strong theoretical or empirical justification and can distort significantly the results, leading to inconsistent estimates. To deal with theses issues, non linear methods are proposed in the literature of gravity model. Amongs them, we can notice the Non linear Least Square (NLS) (Frankel and Wei, 1997), the Gamma Pseudo Maximum Likelihood (GPML) (Manny and Mullay, 2001), the Heckman Sample Selection Model (Heckman, 1979; Linder and de Groot, 2006) or the Poisson Pseudo Maximum Likelihood (PPML) (Santos Silva and Tenreyro, 2006). Santos Silva and Tenreyro (2006) show that the PPML estimator is an efficient estimator allowing to deal with zero values issue and mitigates the heteroskedasticity issue. According to them, in the presence of zero-valued observations and because the logarithmic transformation of the gravity equation, OLS(both truncated and censored OLS) is inconsistent and exhibits a significant bias that does not diminish as the sample size grows, thus confirming its inconsistency (Santos Silva and Tenreyro, 2011). On the other hand, the PPML approach estimates the gravity equation in levels rather than using logarithms, which is said to avoid the issues encountered with OLS under logarithmic transformation. They argue that the PPML estimation is suitable for several reasons: first, the Poisson estimation accounts for heterogeneity in units. Second, the PPML estimation method provides a natural solution for zero-valued observations due to its multiplicative forms. Third, the method prevents the underestimation of large observations flows (in the case of trade data for example) by producing estimates of these observations in levels rather than their logarithms. While Burger et al. 2009, noted that the PPML estimator can be vulnerable to the problem of overdispersion in the dependent variable and excessive zero flows, Santos Silva and Tenreyro (2011) replicated that PPML is consistent and generally performs well even where there is overdispersion in the dependent variable (i.e., when the conditional variance is not equal to the conditional mean), and a high proportion of zeros does not impacts its performance. Additionally, Soren and Bruemmer (2012) argued that PPML performs well under overdispersion and is behaves well bimodal distributed trade data. Similarly, Staub and Winkelmann (2013) found that the PPML estimator is consistent even with an excessive number of zeros. Moreover, the PPML estimator is posited to be less affected by heteroskedasticity compared to other estimators such as GPML or NLS (Martinez-Zarzosso, 2013; Martin and Pham, 2008). Regarding the other estimation techniques, Santos Silva and Tenreyro (2011) found that the GPML is consistent and performs well in Monte Carlo Simulations, even when there are many zero values generated by a constant elasticity model, however, it exhibits a larger bias compared to PPML, suggesting that PPML is the superior estimator. Additionally, Martinez-Zarzoso (2013) observed that GPML can suffer from a significant loss of precision, especially if the variance function is mis-specified or the log-scale residuals exhibit high kurtosis[6]. Furthermore, Santos Silva and Tenreyro (2006) show that while GPML and NLS can address zero values issue, NLS technique assigns greater weight to noisier observations, decreasing the estimator's efficiency. PPML, on the other hand, assigns equal weight to all observations and assumes the conditional variance is proportional to the conditional mean. In contrast, both GPML and NLS give more weight to observations with larger means, due to the more pronounced curvature of the conditional mean for these observations, which typically have larger variances and are therefore noisier. Additionally, they noted that NLS can be very inefficient as it generally ignores the heteroskedasticity in the data. The Heckman selection model, frequently used in literature shows also some limits. Indeed, transforming the model into logarithmic form before estimation can lead to biased coefficients (Haworth and Vincent, 1979; Santos Silva and Tenreyro, 2006). Additionally, Flam and Nordstrom (2011) and Santos Silva and Tenreyro (2009) argued that this model do not account for heteroskedasticity.

Regarding the advantages offered by the PPML estimation, our estimation technique will rely on this estimation. The model with bilateral climate finance flows and control variables is described as follows:

$$lnCFinance_{ijt} = lnX_{it}\beta + lnY_{jt}\theta + lnZ_{ijt}\delta + u_i + u_j + \epsilon_{ijt} \tag{3}$$

$Cfin_{ijt}$ is related to climate finance flows from country i to country j at time t; $i = 1, ..., N$ is related to the numbers of provider countries; $j = 1, ..., N$, the number of recipient countries and $t = 1, ..., T$, the number of time periods. X_{it} is related to variables of provider countries such as Gross domestic product per Capita (GdpcP). Y_{jt} is related to recipient countries variables such as Gross domestic product (GdpcR), Climate Vulnerability (CV03) or Population (Pop). Z_{ijt} is related to common variables between country i and country j. We include to the model common dummy variables such as colonial ties in order to take into account political links, Trade agreement or Bilateral investment treaties. u_i is related to provider country's fixed effects, u_j is related to recipient country's fixed effects and ϵ_{ijt} is related to the error term.
Following the Poisson Pseudo Maximum Likelihood (PPML) estimation, allowing to deal with problem of heteroskedasticity and zero values (Silva and Tenreyro, 2006), the model is transformed to

[6] Kurtosis measures the concentration of data in the tails of the distribution compared to a normal distribution. In other words, it indicates whether the data has more or fewer extreme values than expected in a normal distribution. Kurtosis is important for evaluating the normality of residuals in regression models. High kurtosis values can indicate that the residuals have heavier tails, which can affect statistical tests and predictions.

have the dependent variable in level and is specified as follows:

$$CFinance_{ijt} = exp\{lnX_{it}\beta + lnY_{jt}\theta + lnZ_{ijt}\delta + u_i + u_j + \epsilon_{ijt}\} \tag{4}$$

The model is estimated separately with three dependent variables that are total climate finance (CFinance), Grants and Loans. It's estimated through an augmented estimation technique known as PPMLHDFE (Poisson Pseudo Maximum Likelihood with High Dimension Fixed Effects) from Correia et al. 2020 allowing to control for multiple fixed effects. This estimator has the advantage to take into account the advantage of the PPML estimator and allows for controlling multiple levels of fixed effects and multiple sources of heterogeneity.

4.3 Baseline results

Table 2 outlines the determinants of international climate finance, including total climate finance (CFinance), Grants and Loans. The coefficient for the climate vulnerability variable (CV03) is not significant across all categories, suggesting that vulnerable countries are not more likely to receive climate finance. The coefficient for the income level of recipient countries (GdpcR) is negative but not significant for total climate finance flows and loans, indicating that climate finance is generally not directed towards countries with lower GDP per capita. However, grants are more likely to be allocated to these lower income countries, confirming the hypothesis from the stylized facts in section 3. Exports from donor to recipient countries play a significant role in the allocation of climate finance, as supported by previous studies (Bayramoglu et al., 2023; Weiler et al., 2018). Similarly, the positive coefficient for trade agreements (RTA) in the context of total climate finance and loans suggests that donor countries tend to allocate climate aid, especially loans, to countries with which they share trade relationships. Additionally, the positive and significant coefficient for Bilateral investment treaties (BIT) across all climate finance flows indicates that investment interests of donor countries contribute significantly influence the provision of climate finance. These findings imply that economic interests of donor countries play a substantial role in the allocation of climate finance. The results also indicate that donor countries contributing more to global warming through higher greenhouse gas emissions are not more likely to provide climate finance, as shown by the negative but not significant coefficient for the GHGP variable in total climate finance and grants. Similarly, recipient countries that contribute more to global warming tend to receive less climate finance overall, particularly in the form of loans. The positive coefficients for colonial ties (Col) in total climate finance and grants suggest that donor countries are inclined to support their former colonies. The negative and significant coefficient for the Diplomatic Disagreement variable (DiploD) across all climate finance flows indicates that donor countries are more likely to assist politically aligned nations. Geographical proximity (Distcap) also plays a significant role in climate finance distribution; recipients geographically closer to donor countries are likely to receive more climate finance, particularly in the form of grants. For example, and as mentioned from stylized facts in section 3, several donor countries, such as Australia, Japan or New Zealand, frequently assist countries within their own region (see Figures 9, 10 and 11). However, loans appear to be distributed independently of geographical proximity. The coefficient for natural resources rent (Nrent) is significant at 5% level for grants but not significant for total climate finance and loans, suggesting that resource-rich countries are primarily likely to receive grants which constitute a small portion of total climate finance (see Figure 1). An other finding is that recipient countries with large populations (Pop) and those that receive development aid (ODA) are more likely to receive climate aid. Regarding recipient merits, the level of institutional quality (IQ) appears to play a key role in the provision of total climate aid, particularly grants. A strong institutional framework can provide assurance to donor countries regarding the effective management of climate aid.

Variables	CFinance	Grants	Loans
CV03 (lagged)	-9.3616	-5.3363	-18.1782
	(7.3136)	(6.1619)	(12.0398)
Exports (lagged)	0.2429***	0.2443***	0.3927***
	(0.0523)	(0.0379)	(0.1025)
GdpcR	-0.0403	-0.5209*	0.2822
	(0.5224)	(0.2811)	(0.9052)
GdpcP	2.4427**	0.3478	6.6059***
	(1.1032)	(0.4722)	(2.2935)
Pop	2.8551***	2.7259***	3.5721***
	(0.4771)	(0.4928)	(0.0105)
Nrent	0.1405	0.2086**	0.1474
	(0.0992)	(0.0747)	(0.1576)
RTA	0.4908***	0.0922	0.5476***
	(0.1282)	(0.0985)	(0.2105)
BIT	0.2165**	0.2468***	0.2413*
	(0.0901)	(0.0859)	(0.1252)
ODA (lagged)	1.3331***	2.1086***	1.0183***
	(0.3989)	(0.4131)	(0.2769)
GHGP (lagged)	-0.9116	-0.4931	-2.3489
	(0.8225)	(0.5124)	(1.5275)
GHGR (lagged)	-1.0591**	-0.0921	-1.8964**
	(0.4239)	(0.3381)	(0.7265)
IQ	4.4039**	4.6234***	3.6434
	(2.0439)	(1.1568)	(3.0046)
Col	0.3296**	1.0115***	-0.0103
	(0.1781)	(0.1847)	(0.3782)
DiploD (lagged)	-0.7012**	-0.6538***	-0.7181*
	(0.3243)	(0.2332)	(0.4576)
Distcap	-0.4727***	-0.4681***	-0.1351
	(0.1479)	(0.1002)	(0.2673)
Observations	79246	79246	79246
Pseudo R-squared	0.7443	0.6138	0.7609
Log pseudolikelihood	-288186737.9	-100988589	-185730074.5
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** $p<0.01$, significant at 1%, ** $p<0.05$, significant at 5%, * $p<0.1$ significant at 10%.

Table 2: Baseline result of potential determinants of international climate finance

4.4 Robustness Checks

In this section, we subject our baseline results to a series of robustness tests. First, we re-evaluate the baseline results without including lags, without GHG emissions and with the inclusion of recipient imports instead of donors exports. Second, apply a dynamic probit model. Third, we use alternative vulnerability indicators. Fourth, we focus specifically on resource-rich countries, defined as those with natural resource rents exceeding 10% of GDP, a criterion suggested by the World Bank Group. Fifth, we estimate the baseline model using data from the ten largest donor countries. Sixth, we estimate the baseline model for the most recipient regions. Seventh, we test the baseline results using data from Small Islands Countries. Finally, we consider allocations based on targeted objectives by distinguishing between climate adaptation finance and climate mitigation finance.

4.4.1 Estimations without lags, without GHG emissions and with recipient's imports

We estimate the baseline model without including lags, without considering GHG emissions and using recipient imports instead of provider exports. The estimation without lags yields results similar to the baseline. For the estimation without GHG emissions, we conducted this test because we suspected a correlation between GHG emissions and GDP per capita (as GDP per capita increases, GHG emissions may rise due to industrialization, transportation, or urbanization), which could influence the baseline results. However, the findings remain consistent with the baseline, showing that the most vulnerable countries are not likely to receive climate aid. Additionally, the signs and significance of the coefficients for other variables are very similar to the baseline results. Regarding the estimation using recipient imports, we performed this test to compare trade flows reported by providers and recipients. Each reporting country specifies the trade volume it has with each of its partner countries, both in terms of exports and imports. The key difference is that exports are reported by the providers as FOB (Free on Board), while imports are reported by the recipients as CIF (Cost, Insurance, and Freight). The results align with the baseline, suggesting that vulnerable countries are not likely to receive climate aid. Similar to provider exports in the baseline results, recipient imports tend to positively influence the provision of climate aid. Therefore, countries that import more from the provider are likely to receive more climate aid. Trade agreements (RTA), investment treaties (BIT), development aid (ODA), institutional quality (IQ), colonial ties (Col), political alignment (DiploD) and geographical distance (Distcap) all play key roles in the provision of climate aid. Compared to loans, grants are more likely to be provided to countries with strong institutional quality and those that share colonial ties, political alignment, and geographical proximity with the provider.

Variables	CFinance	Grants	Loans
CV03	-3.9299	-3.9576	-8.1307
	(7.0312)	(6.6923)	(11.0607)
Exports	0.2228***	0.2425***	0.3107***
	(0.0533)	(0.0404)	(0.1111)
GdpcR	-0.2448	-0.4048	-0.0515
	(0.5008)	(0.3371)	(0.8041)
GdpcP	1.5132	0.9552**	3.5508
	(1.0452)	(0.5257)	(2.2271)
Pop	2.4406***	2.9561***	2.7058***
	(0.4720)	(0.4889)	(0.9921)
Nrent	0.1454	0.1478*	0.1877
	(0.1075)	(0.0854)	(0.1722)
RTA	0.4758***	0.0793	0.4929**
	(0.1282)	(0.1066)	(0.1931)
BIT	0.1920**	0.2441***	0.2182*
	(0.0892)	(0.0889)	(0.1271)
ODA	1.7259***	2.0885***	1.4567***
	(0.4721)	(0.3846)	(0.3732)
GHGP	-1.7136**	-1.6441***	-2.3842
	(0.8225)	(0.5641)	(1.5946)
GHGR	-0.7099*	-0.2391	-1.2545*
	(0.4339)	(0.3456)	(0.7328)
IQ	6.0309***	4.6851***	6.7258**
	(1.8880)	(1.2538)	(2.8902)
Col	0.3366**	1.0104***	0.0464
	(0.1833)	(0.1889)	(0.3995)
DiploD	0.6206	-0.6851**	1.4873***
	(0.4311)	(0.2756)	(0.5329)
Distcap	-0.5176***	-0.4306***	-0.3444
	(0.1471)	(0.1034)	(0.2709)
Observations	79068	79068	79068
Pseudo R-squared	0.7504	0.6108	0.7706
Log pseudolikelihood	-262720385.4	-94948504.49	-166413387.8
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 3: baseline results without lags

Variables	CFinance	Grants	Loans
CV03 (lagged)	-10.0106	-4.9901	-20.2333
	(7.6346)	(6.1081)	(12.6455)
Exports (lagged)	0.2421***	0.2342***	0.4047***
	(0.0512)	(0.0372)	(0.1015)
GdpcR	-0.6514	-0.5551*	-0.9309
	(0.5215)	(0.2901)	(0.8852)
GdpcP	1.9258**	0.1119	4.7769***
	(0.8932)	(0.4639)	(1.7297)
Pop	2.7966***	2.7179***	3.3108***
	(0.4725)	(0.4773)	(0.9789)
Nrent	0.1163	0.2054**	0.1177
	(0.0994)	(0.0731)	(0.1588)
RTA	0.4532***	0.0811	0.4717**
	(0.1297)	(0.0981)	(0.2095)
BIT	0.1965**	0.2351***	0.2088*
	(0.0902)	(0.0852)	(0.1282)
ODA (lagged)	1.3642***	2.1072***	1.0754***
	(0.4031)	(0.4075)	(0.2919)
IQ	4.7062**	4.6051***	4.1611
	(2.1502)	(1.1762)	(3.3262)
Col	0.3356*	1.0223***	-0.0211
	(0.1777)	(0.1846)	(0.3815)
DiploD (lagged)	-0.6627**	-0.6216***	-0.6911
	(0.3317)	(0.2288)	(0.4766)
Distcap	-0.5099***	-0.5032***	-0.1945
	(0.1449)	(0.0992)	(0.2576)
Observations	81466	81466	81466
Pseudo R-squared	0.7434	0.6142	0.7572
Log pseudolikelihood	-292588229	-102000610.5	-190103261
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 4: Baseline estimation without Greenhouse gas emission variables

Variables	CFinance	Grants	Loans
CV03 (lagged)	-8.8445	-5.4067	-17.2433
	(7.2337)	(6.1923)	(11.9098)
Imports (lagged)	0.1503***	0.1967***	0.2772**
	(0.0517)	(0.0368)	(0.1201)
GdpcR	0.1002	-0.4151	0.5157
	(0.5328)	(0.2835)	(0.9108)
GdpcP	2.4218**	0.3421	6.3855***
	(1.0925)	(0.4702)	(2.2758)
Pop	2.8184***	2.6969***	3.4978***
	(0.4725)	(0.4912)	(0.9887)
Nrent	0.1395	0.2086**	0.1588
	(0.0987)	(0.0734)	(0.1551)
RTA	0.4796***	0.0852	0.5129**
	(0.1334)	(0.0991)	(0.2149)
BIT	0.8126**	0.2365***	0.2319*
	(0.0912)	(0.0867)	(0.1302)
ODA (lagged)	1.3285***	2.1418***	1.0179***
	(0.4061)	(0.4031)	(0.2752)
GHGP (lagged)	-0.9397	-0.4936	-2.4213
	(0.8228)	(0.5111)	(1.5257)
GHGR (lagged)	-1.0969**	-0.1622	-1.9839***
	(0.4266)	(0.3349)	(0.7161)
IQ	4.3318**	4.4319***	3.7211
	(2.1319)	(1.1374)	(3.2028)
Col	0.4332**	1.0504***	0.1611
	(0.1737)	(0.1853)	(0.3571)
DiploD (lagged)	-0.7081**	-0.6821***	-0.6993
	(0.3168)	(0.2292)	(0.4438)
Distcap	-0.6337***	-0.5658***	-0.3613
	(0.1504)	(0.0984)	(0.2795)
Observations	79246	79246	79246
Pseudo R-squared	0.7429	0.6124	0.7593
Log pseudolikelihood	-289676161.4	-101349587.5	-187013632.6
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** $p<0.01$, significant at 1%, ** $p<0.05$, significant at 5%, * $p<0.1$ significant at 10%.

Table 5: Baseline estimation with recipient's imports

4.4.2 Use of alternative estimation: Dynamic Probit Model

We employ a dynamic probit model to assess the likelihood of recipient countries receiving climate aid based on the determinants used in the baseline results. Unlike a standard probit model, the dynamic probit model includes the lag of the dependent variable among the explanatory variables. This model is particularly valuable when analyzing data with temporal dependencies or persistence effects, which may be the case in climate finance flows. The inclusion of past values of the dependent variable allows to capture the effect of historical events on current outcomes, offering a clearer understanding of how past experiences influence present probabilities. By incorporating lagged values, the model can control for unobserved effects that vary over time and mitigate omitted variable bias (Arrelano and Bond, 1991; Roodman, 2009; Cameron and Trivedi, 2021). Compared to static model, dynamic probit model is supported to handle complex panel data structures and enhance forecasting accuracy by considering the temporal dimension of data (Wooldridge, 2002; Bun and Makridis, 2022). Here, the dependent variables - CFinance, Grants, and Loans - are treated as binary, taking a value of 1 if the recipient country receives climate finance and 0 otherwise. The model used and its estimation follow the approach outlined by Albarran et al. (2019) and Albarran et al. (2020). Albarran et al. 2019 implement the model by addressing challenges associated with unbalanced panels and the correlation between random effects and explanatory variables, which can complicate estimation. They opt for random effects rather than fixed effects due to their ability to efficiently use both between- and within-unit variations, their robustness to unbalanced data, and the flexibility their offer for modeling temporal dynamics. This choice helps overcome some limitations of fixed effects, particularly regarding missing data and computational complexity (Cameron and Trivedi, 2005; Baltagi, 2008; Wooldridge, 2010; Greene, 2012). Estimation is conducted for each sub-panel, with the common parameters being obtained via the minimum distance method. This approach is asymptotically equivalent to the maximum likelihood estimator, but reduces computational complexity. The model is structured as follows:

$$CFin_{ijt} = \phi CFin_{ijt-1} + X_{it}\gamma + Y_{jt}\lambda + Z_{ijt}\varphi + \epsilon_{ijt} \tag{5}$$

Where $CFin$ represents the binary dependent variables: CFinance, Grants, and Loans. X_{it} refers to the variables specific to provider countries, Y_{jt} relates to the recipient countries' specific variables, Z_{ijt} encompasses the shared variables between countries i and j and ϵ_{ijt} represents to the error term. We estimated the model both with and without lags of other explanatory variables (Tables 6 and 7, respectively). The results align with the baseline findings, indicating that countries vulnerable to climate change unlikely to receive climate aid. Consistent with the benchmark results, the probability of receiving climate aid is positively associated with factors such as the provider's exports, trade agreements (RTA), investment treaties (BIT), development aid, institutional quality and colonial ties, as shown by the positive and significant coefficients for these variables when considered for the "CFinance" dummy variable. When comparing grants and loans, having a colonial link with the provider country increases the likelihood of receiving grants, while having political proximity (DiploD) with the provider countries increases the likelihood of receiving loans. A new insight from this model is that countries that have previously received climate aid are more likely to receive it again in the future.

Variables	CFinance	Grants	Loans
CFinance (lagged)	1.1457***		
	(0.0185)		
Grants (lagged)		1.1551***	
		(0.0186)	
Loans (lagged)			0.5853***
			(0.0646)
CV03 (lagged)	0.2388	0.1912	0.6798
	(0.3379)	(0.3383)	(0.8855)
Exports (lagged)	0.1448***	0.1445***	0.3884***
	(0.0057)	(0.0057)	(0.0248)
GdpcR	-0.1581***	-0.1632***	-0.3425***
	(0.0289)	(0.0289)	(0.0775)
GdpcP	0.6817***	0.6802***	-0.1423
	(0.0343)	(0.0344)	(0.0964)
Pop	2.4531***	2.4478***	1.9608***
	(0.0769)	(0.0771)	(0.2271)
Nrent	-0.0119	-0.0131	-0.0149
	(0.0145)	(0.0145)	(0.0384)
RTA	0.0459*	0.0514*	0.1956***
	(0.0284)	(0.0285)	(0.0696)
BIT	0.2319***	0.2215***	0.3196***
	(0.0321)	(0.0321)	(0.0682)
ODA (lagged)	0.1582***	0.1581***	1.9015***
	(0.0521)	(0.0521)	(0.1981)
GHGP (lagged)	-0.3365***	-0.3401***	-0.6319***
	(0.0375)	(0.0376)	(0.0972)
GHGR (lagged)	-0.2064***	-0.2008***	-0.1751**
	(0.0304)	(0.0304)	(0.0848)
IQ	0.7011***	0.6581***	1.7606***
	(0.1905)	(0.1907)	(0.5464)
Col	0.5021***	0.5001***	0.1303
	(0.0825)	(0.0825)	(0.1346)
DiploD (lagged)	0.0553	0.0683	-0.3809***
	(0.0471)	(0.0472)	(0.1164)
Distcap	0.1549***	0.1573***	0.3271***
	(0.0272)	(0.0273)	(0.0644)
Observations	79246	79246	79246
Log likelihood	-21552.52	-21428.46	-2660.98
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 6: Dynamic Probit Model

Variables	CFinance	Grants	Loans
CFinance (lagged)	1.1401*** (0.0191)		
Grants (lagged)		1.1503*** (0.0192)	
Loans (lagged)			0.4652*** (0.0635)
CV03	0.2506 (0.3378)	0.2169 (0.3381)	0.6677 (1.0981)
Exports	0.1528*** (0.0058)	0.1515*** (0.0058)	0.4732*** (0.0291)
GdpcR	-0.2058*** (0.0292)	-0.2085*** (0.0292)	-0.4385*** (0.0953)
GdpcP	0.6531*** (0.0344)	0.6511*** (0.0344)	-0.1966 (0.1202)
Pop	2.6179*** (0.0818)	2.6116*** (0.0819)	2.5086*** (0.2635)
Nrent	-0.0157 (0.0148)	-0.0163 (0.0149)	-0.0284 (0.0464)
RTA	0.0566* (0.0293)	0.0611** (0.0294)	0.2089** (0.0822)
BIT	0.2226*** (0.0323)	0.2136*** (0.0323)	0.3634*** (0.0833)
ODA	0.1037** (0.0521)	0.0979* (0.0523)	1.2932*** (0.2094)
GHGP	-0.3273*** (0.0376)	-0.3291*** (0.0377)	-0.7339*** (0.1227)
GHGR	-0.1705*** (0.0308)	-0.1662*** (0.0308)	-0.1678 (0.1033)
IQ	0.8362** (0.1921)	0.7881*** (0.1921)	2.2309*** (0.6606)
Col	0.4668*** (0.0817)	0.4681*** (0.0815)	0.1188 (0.1893)
DiploD	0.1113** (0.0476)	0.1121** (0.0477)	-0.2813** (0.1423)
Distcap	0.1642*** (0.1479)	0.1666*** (0.0274)	0.3932*** (0.0824)
Observations	75791	75791	75791
Log likelihood	-20478.52	-20361.09	-2456.78
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** $p<0.01$, significant at 1%, ** $p<0.05$, significant at 5%, * $p<0.1$ significant at 10%.

Table 7: Dynamic Probit Model without lags of other explanatory variables

4.4.3 Use of alternative climate Vulnerability indicators: ND-GAIN Vulnerability indicator (NDG) and World Risk Index (WRI)

We assess the baseline results using alternative vulnerability indicators: the NDG-GAIN Vulnerability indicator (NDG) and the World Risk Index (WRI). The NDG indicator ranges from 0 to 1, with higher values indicating greater vulnerability. The WRI is not confined to a specific range, but higher values similarly reflect increased climate vulnerability. In the estimation using the NDG indicator (Table 8), the coefficient for NDG indicator is negative and significant for total climate finance and loans, suggesting that more vulnerable countries generally receive less climate finance, particularly in the form of loans. As in the baseline result, provider exports, trade agreements (RTA), investment treaties (BIT), development aid, institutional quality (IQ), colonial ties (Col), political alignment (DiploD) and geographical proximity (Distcap) all play a role in the allocation of climate aid. Grants are specially likely to go to countries with strong institutional frameworks and those that share colonial, political and geographical proximity with the provider. Compared to grants, loans are more likely to be directed towards countries that have a trade agreement with the provider. Similarly, the estimation using the WRI indicator (Table 9) aligns with the baseline results. The most vulnerable countries are still unlikely to receive climate aid. Provider exports, trade agreements, investment treaties, development aid, institutional quality, colonial ties, political proximity, and geographical proximity continue to significantly influence the distribution of climate aid. Grants, in particular, are more often given to countries with good institutional quality and those that share colonial, political and geographical ties with the provider. As with NDG estimation, loans are more likely to be allocated to countries that share a trade agreement with the provider.

Variables	CFinance	Grants	Loans
NDG (lagged)	-14.6488*	3.3155	-31.4223**
	(8.7042)	(6.1797)	(13.3449)
Exports (lagged)	0.2393***	0.2443***	0.3792***
	(0.0521)	(0.0381)	(0.1007)
GdpcR	-0.2457	-0.4921	-0.1556
	(0.5032)	(0.3101)	(0.8579)
GdpcP	2.4868**	0.3537	6.7017***
	(1.1001)	(0.4719)	(2.2554)
Pop	2.7018***	2.7062***	2.9591***
	(0.4771)	(0.4923)	(1.0156)
Nrent	0.1376	0.2198**	0.1487
	(0.0981)	(0.0761)	(0.1571)
RTA	0.4947***	0.0977	0.5544***
	(0.1275)	(0.0982)	(0.2067)
BIT	0.2194**	0.2462***	0.2518**
	(0.0906)	(0.0859)	(0.1268)
ODA (lagged)	1.3111***	2.1121***	0.9751***
	(0.3888)	(0.4097)	(0.2544)
GHGP (lagged)	-0.9307	-0.4935	-2.4109
	(0.8213)	(0.5128)	(1.5058)
GHGR (lagged)	-1.0653**	-0.0848	-1.9215***
	(0.4118)	(0.3385)	(0.6657)
IQ	4.7686**	4.6997***	4.5208
	(1.9663)	(1.1706)	(2.8679)
Col	0.3341**	1.0114***	0.0086
	(0.1775)	(0.1847)	(0.3704)
DiploD (lagged)	-0.7251**	-0.6575***	-0.7271
	(0.3318)	(0.2339)	(0.4725)
Distcap	-0.4744***	-0.4676***	-0.1431
	(0.1486)	(0.1002)	(0.2697)
Observations	79246	79246	79246
Pseudo R-squared	0.7444	0.6138	0.7617
Log pseudolikelihood	-287978714.4	-100994438.9	-185140815.8
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 8: Estimation with ND-GAIN vulnerability indicator

Variables	CFinance	Grants	Loans
WRI (lagged)	-0.2371	-0.3028	-0.4858
	(0.2699)	(0.2376)	(0.4295)
Exports (lagged)	0.2418***	0.2441***	0.3863***
	(0.0521)	(0.0379)	(0.1012)
GdpcR	-0.0951	-0.5195*	0.2001
	(0.5339)	(0.2836)	(0.9315)
GdpcP	2.4651**	0.3581	6.6251***
	(1.1089)	(0.4719)	(2.3055)
Pop	2.9036***	2.6912***	3.7349***
	(0.4817)	(0.4888)	(0.9793)
Nrent	0.1528	0.2183**	0.1691
	(0.0994)	(0.0794)	(0.1587)
RTA	0.4951***	0.0961	0.5537***
	(0.1298)	(0.0981)	(0.2101)
BIT	0.2174**	0.2481***	0.2461**
	(0.0899)	(0.0859)	(0.1251)
ODA (lagged)	1.3424***	2.0958***	1.0379***
	(0.4037)	(0.4094)	(0.2831)
GHGP (lagged)	-0.9074**	-0.4961	-2.2896
	(0.8295)	(0.5128)	(1.5468)
GHGR (lagged)	-1.1044***	-0.0634	-2.0627***
	(0.4187)	(0.3349)	(0.7085)
IQ	4.5244**	5.0278***	4.0306
	(1.9516)	(1.2306)	(2.8461)
Col	0.3304*	1.0121***	-0.0041
	(0.1779)	(0.1848)	(0.3766)
DiploD (lagged)	-0.6988**	-0.6594***	-0.6911
	(0.3283)	(0.2317)	(0.4757)
Distcap	-0.4735***	-0.4679***	-0.1433
	(0.1475)	(0.1003)	(0.2649)
Observations	79246	79246	79246
Pseudo R-squared	0.7442	0.6139	0.7609
Log pseudolikelihood	-288221277.4	-100971998.4	-185768840.5
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** $p<0.01$, significant at 1%, ** $p<0.05$, significant at 5%, * $p<0.1$ significant at 10%.

Table 9: Estimation with World Risk Index (WRI)

4.4.4 Estimation regarding resource-rich countries

We evaluate now the potential determinants of international climate finance by focusing specifically on resource-rich countries, defined by the World Bank Group as nations where natural resource rents exceed 10% of GDP on average over the last three years. These countries face multiple challenges. In addition to their susceptibility to climate change events such as droughts, floods or extreme temperatures and therefore need financial assistance for adaptation actions, many are major producers of natural resources like oil, gas, and minerals. The extraction and utilization of these resources are often designed as significant drivers of greenhouse gas emissions

(Mason and William, 2020; Bardoux et al., 2016), contributing to global warming and exacerbating their vulnerability to climate change through environmental degradation (Afolabi, 2023; Agboola et al., 2021). Providing financial assistance to these countries for economic diversification and climate-friendly projects could yield substantial benefits by contributing to climate mitigation efforts. However, our results indicate that vulnerable countries within this group are not prioritized in the allocation of climate finance. Generally, climate finance tends to be directed towards countries that receive more exports from provider nations, have established investment treaties, share colonial ties, already received development aid, possess strong institutional frameworks, and are geographically proximate to the providers. Moreover, the coefficient associated with the natural resources variable (Nrent) is not significant for total climate finance, suggesting that resource-rich countries are not more likely to receive increased climate aid. Grants are predominantly allocated to countries that are politically aligned with the providers and resource-rich countries are only likely to receive grants (as indicated by the positive and significant coefficient for the "Nrent" variable in the case of Grants) even though grants constitute a small portion of total climate finance (see Figure 1). In contrast, loans are mainly provided to countries that have investment treaties with the providers. Considering that climate finance is often directed towards countries with high institutional quality, it is imperative for resource-rich nations to enhance their institutional frameworks by promoting transparency, combating corruption, and ensuring effective governance. Such improvements could serve as assurances for provider countries regarding the efficient and responsible management of climate aid.

Variables	CFinance	Grants	Loans
CV03 (lagged)	-5.7222	-13.2983	9.0535
	(9.1213)	(10.2531)	(19.6748)
Exports (lagged)	0.1556***	0.2118***	0.0281**
	(0.0589)	(0.0484)	(0.0136)
GdpcR	0.2161	0.4435	-0.2886
	(0.4971)	(0.3859)	(1.7336)
GdpcP	0.0742	-0.6855	7.0076*
	(1.1249)	(0.7799)	(4.3521)
Pop	4.0081**	4.7365***	8.4219*
	(1.6318)	(0.9041)	(5.1237)
Nrent	0.0056	0.3404**	-1.1029**
	(0.1774)	(0.1426)	(0.4346)
RTA	0.1526	-0.1398	0.1746
	(0.2521)	(0.2107)	(0.6199)
BIT	0.4973**	0.1029	0.5947*
	(0.1981)	(0.1584)	(0.3552)
ODA (lagged)	2.1796***	2.6054***	1.3461
	(0.5181)	(0.4423)	(0.9113)
GHGP (lagged)	-0.3841	-1.2634	-1.9997
	(0.9545)	(0.8193)	(3.0927)
GHGR (lagged)	0.0162	-0.5524	-1.6837
	(0.4781)	(0.4262)	(1.6044)
IQ	10.7119***	4.3538**	25.1971***
	(2.2183)	(1.8811)	(6.9197)
Col	1.0542***	1.0006***	3.4955***
	(0.3228)	(0.3465)	(0.7328)
DiploD (lagged)	-0.4619	-0.8216**	-0.2221
	(0.5408)	(0.4132)	(1.2858)
Distcap	-0.8989***	-0.8977***	-1.5691**
	(0.2801)	(0.2019)	(0.6414)
Observations	24834	24834	24834
Pseudo R-squared	0.6270	0.6425	0.6594
Log pseudolikelihood	-57465044.02	-27845888.13	-25042064.94
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** $p<0.01$, significant at 1%, ** $p<0.05$, significant at 5%, * $p<0.1$ significant at 10%.

Table 10: Estimation with Resource-rich countries

4.4.5 Estimation with the 10 largest provider countries

We estimate the baseline model for the ten largest provider countries: Japan, Germany, France, the United States, Norway, the United Kingdom, South Korea, the Netherlands, Australia and Sweden. These countries contribute significantly, accounting for approximately 90% of total climate finance. The results are consistent with the baseline findings, indicating that vulnerable countries are not prioritized in the allocation of climate aid, as evidenced by the negative and insignificant coefficient associated with the vulnerability indicator (CV03). Factors such as exports from provider countries, trade agreements (RTA), investment treaties (BIT), development aid (ODA), institutional quality (IQ), political proximity (DiploD) and colonial ties generally influence the allocation of climate aid. In the specific case of grants and loans, grants tend to be particularly directed towards countries with lower GDP per capita, those with strong institutional quality, countries with colonial ties to the provider and those geographically closer to the provider, similar to the benchmark results.

Variables	CFinance	Grants	Loans
CV03 (lagged)	-7.2975	-0.2781	-15.3726
	(7.9602)	(7.5461)	(11.9102)
Exports (lagged)	0.2629***	0.2668***	0.3951***
	(0.0613)	(0.0496)	(0.1057)
GdpcR	-0.0476	-0.6185**	0.1972
	(0.5746)	(0.3106)	(0.9184)
GdpcP	5.1423***	2.0875*	7.5522***
	(1.8336)	(1.0821)	(2.8862)
Pop	3.1986***	2.9971***	3.5217***
	(0.5406)	(0.5489)	(1.0522)
Nrent	0.1285	0.1748*	0.1379
	(0.1114)	(0.0909)	(0.1597)
RTA	0.5495***	0.178*	0.5653***
	(0.1401)	(0.1084)	(0.2163)
BIT	0.2205**	0.1837*	0.2532**
	(0.0958)	(0.0995)	(0.1276)
ODA (lagged)	1.2378***	1.8973***	1.0033***
	(0.3622)	(0.4346)	(0.2733)
GHGP (lagged)	-2.4113**	-2.7013***	-2.6318*
	(0.9626)	(0.5173)	(1.5774)
GHGR (lagged)	-1.1525**	-0.0032	-1.8961**
	(0.4711)	(0.4076)	(0.7367)
IQ	4.4788**	5.0348***	3.6077
	(2.1624)	(1.3071)	(3.0224)
Col	0.2418	0.7436***	0.0171
	(0.1939)	(0.2045)	(0.4003)
DiploD (lagged)	-0.7696**	-0.5186*	-0.8574*
	(0.3571)	(0.2827)	(0.4471)
Distcap	-0.3734**	-0.3775***	-0.1132
	(0.1681)	(0.1185)	(0.2748)
Observations	26490	26490	26490
Pseudo R-squared	0.7164	0.5931	0.6844
Log pseudolikelihood	-237564232.3	-65364213.94	-175651188.2
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** $p<0.01$, significant at 1%, ** $p<0.05$, significant at 5%, * $p<0.1$ significant at 10%.

Table 11: Estimation for the 10 most provider countries

4.4.6 Estimation for the most recipient regions: Asia, Africa and America

We focus on the most recipient regions: Asia (Table 12), Africa (Table 13) and the Americas (Table 14). The findings suggest that vulnerable countries in Asia are not prioritized in the allocation of climate finance, as indicated by insignificance of the vulnerability indicator (CV03) across all climate finance flows. Similar to the benchmark results, factors such as exports from provider countries, trade agreements (RTA), investment treaties (BIT), development aid (ODA) and colonial ties tend to positively influence climate aid allocation to this region. Political proximity (DiploD) also appears to contribute to the provision of climate aid, particularly in the form of loans. Additionally, provider countries tend to grant aid to nations geographically closer to them, as suggested by the negative and significant coefficient associated with the distance between countries (Distcap). In Africa, vulnerable countries similarly do not appear to be prioritized in the provision of climate aid. Factors such as provider exports, development aid, and institutional quality play key roles in the allocation of all type of climate finance in this region. Investment treaties (BIT), colonial ties (Col) and Political proximity (DiploD) particularly influence the distribution of grants. For the Americas, the trend continues: vulnerable countries in this region are also not prioritized in receiving climate aid. As in Asia and Africa, exports from provider countries, development aid, and colonial ties generally influence the allocation of climate aid. Grants are particularly allocated to countries with low GDP per capita, strong institutional quality, and geographical proximity to the provider countries. Loans, on the other hand, are particularly provided to countries that share investment treaties and political alignment with the provider country.

Variables	CFinance	Grants	Loans
CV03 (lagged)	-16.6947	-1.2236	-27.1106
	(16.1462)	(11.6916)	(24.2386)
Exports (lagged)	0.1611*	0.0243*	0.3848**
	(0.0984)	(0.0101)	(0.1588)
GdpcR	0.6905	-1.2642***	1.1462
	(0.8622)	(0.4449)	(1.2183)
GdpcP	4.2346**	0.3098	8.1681**
	(2.0106)	(1.1724)	(3.3847)
Pop	3.0697***	1.5428	3.5319*
	(1.1234)	(1.1377)	(2.0635)
Nrent	0.3009	0.2607**	0.3244
	(0.2851)	(0.1258)	(0.2642)
RTA	0.5691**	0.4155**	0.5255*
	(0.2544)	(0.1915)	(0.3255)
BIT	0.1967*	0.2851**	0.2719*
	(0.1236)	(0.1248)	(0.1701)
ODA (lagged)	0.9867***	1.1518***	0.8694***
	(0.2678)	(0.4114)	(0.2391)
GHGP (lagged)	-1.9109	-0.3756	-3.8982*
	(1.3393)	(0.8852)	(2.1307)
GHGR (lagged)	-1.5153**	0.4801	-2.5841**
	(0.7019)	(0.5714)	(1.0127)
IQ	3.4172	7.8149***	1.8233
	(3.1358)	(1.9099)	(3.5598)
Col	0.5099*	0.9418***	0.9699**
	(0.2621)	(0.3057)	(0.3913)
DiploD (lagged)	-1.1847**	-0.7231	-1.2318**
	(0.4825)	(0.5017)	(0.5741)
Distcap	-0.3205	-0.6215***	-0.0864
	(0.3039)	(0.2055)	(0.4182)
Observations	21508	21508	21508
Pseudo R-squared	0.8109	0.6463	0.7926
Log pseudolikelihood	-122506130.8	-30103569.24	-93698499.81
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** $p<0.01$, significant at 1%, ** $p<0.05$, significant at 5%, * $p<0.1$ significant at 10%.

Table 12: Estimation for Asia

Variables	CFinance	Grants	Loans
CV03 (lagged)	5.1146	-3.8699	18.9301
	(10.1297)	(9.4862)	(15.5385)
Exports (lagged)	0.2934***	0.1693***	0.9153***
	(0.0701)	(0.0443)	(0.1245)
GdpcR	0.2269	0.1989	0.9614
	(0.4194)	(0.3681)	(1.6756)
GdpcP	0.1054	-0.0694	1.7934
	(0.7992)	(0.5347)	(4.2251)
Pop	3.0264***	3.3625***	6.1825***
	(0.7784)	(1.0782)	(2.2118)
Nrent	0.2323	0.1671	0.1959
	(0.1576)	(0.1196)	(0.2759)
RTA	0.2413	0.0653	0.8723**
	(0.2112)	(0.1332)	(0.3689)
BIT	0.3221**	0.2123*	-0.3844
	(0.1352)	(0.1205	(0.2596)
ODA (lagged)	2.6016***	3.6976***	-1.4355**
	(0.6169)	(0.5207)	(0.7046)
GHGP (lagged)	0.4261	-0.6687	4.7833
	(0.9737)	(0.7347)	(4.3561)
GHGR (lagged)	0.1817	-0.3334	0.6389
	(0.5321)	(0.4775)	(1.5531)
IQ	6.5849***	2.8628*	14.0937***
	(2.4641)	(1.7107)	(5.2936)
Col	0.3468	0.7977***	-0.7544**
	(0.2176)	(0.2611)	(0.3751)
DiploD (lagged)	-1.0653**	-1.1167***	-1.8012
	(0.4467)	(0.3551)	(1.1564)
Distcap	0.5123	-0.3437	1.7694
	(0.3281)	(0.3951)	(0.4667)
Observations	30456	30456	30456
Pseudo R-squared	0.6510	0.6280	0.6591
Log pseudolikelihood	-77689688.86	-41515125.18	-35075278.11
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 13: Estimation for Africa

Variables	CFinance	Grants	Loans
CV03 (lagged)	5.0221	-3.5964	21.6038
	(19.0783)	(15.2153)	(37.7793)
Exports (lagged)	0.5151***	0.4356***	0.7881***
	(0.1127)	(0.1229)	(0.2194)
GdpcR	0.1621	-1.7782***	2.9176
	(1.0149)	(0.5431)	(2.3717)
GdpcP	0.9791	1.2292	3.8966
	(2.4791)	(1.2957)	(7.8031)
Pop	1.2611	1.0756	3.2471
	(2.9094)	(1.7283)	(6.3571)
Nrent	-0.3885**	-0.0025	-0.6465**
	(0.1635)	(0.1589)	(0.3116)
RTA	0.0446	0.0397	0.2765
	(0.2291)	(0.1741)	(0.3728)
BIT	0.2732*	0.0659	0.2052*
	(0.1786)	(0.2416)	(0.1999)
ODA (lagged)	3.3245***	3.0682***	2.6036**
	(0.8141)	(0.5793)	(1.1931)
GHGP (lagged)	2.9719**	0.3647	5.7257
	(1.4826)	(1.1145)	(4.6139)
GHGR (lagged)	-2.8965**	-0.7451	-3.1774
	(1.2111)	(0.9892)	(2.5271)
IQ	8.2653**	6.2671**	7.8083
	(3.6197)	(2.7426)	(6.6725)
Col	1.1375***	0.6296*	1.2239*
	(0.3684)	(0.5197)	(0.6989)
DiploD (lagged)	-0.8746	-0.3012	-1.8495*
	(0.7767)	(0.4271)	(1.4271)
Distcap	0.2138	-0.9247*	3.7228***
	(0.7811)	(0.5927)	(1.4341)
Observations	18094	18094	18094
Pseudo R-squared	0.7184	0.6688	0.6813
Log pseudolikelihood	-38367992.3	-13929166.56	-23830171.95
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** $p<0.01$, significant at 1%, ** $p<0.05$, significant at 5%, * $p<0.1$ significant at 10%.

Table 14: Estimation for America

4.4.7 Estimation for Small Islands Countries

We focus on Small Island countries which appear to be among most vulnerable nations and are particularly susceptible to sea-level rise and flooding. Despite their critical geographic situation, these countries are also not prioritized in the provision of climate finance. The coefficient associated with the vulnerability indicator (CV03) is not significant across all climate finance flows. Factors such as donor exports, investment treaties (BIT) and institutional quality seem to positively influence the allocation of climate finance, especially in the form of loans to these countries. Additionally, colonial ties (Col) and geographical proximity also play a significant role in the provision of climate finance, particularly in the distribution of grants.

Variables	CFinance	Grants	Loans
CV03 (lagged)	4.4866	-2.2377	9.9771
	(11.9613)	(12.3814)	(14.5956)
Exports (lagged)	0.3397***	0.1706***	0.7605***
	(0.1002)	(0.0549)	(0.1957)
GdpcR	-0.7739	-1.1128	0.8133
	(0.9152)	(0.9331)	(3.5853)
GdpcP	0.7328	0.4718	-1.1055
	(3.0473)	(1.9415)	(7.8907)
Pop	4.5041	2.9561***	-3.8469
	(3.0629)	(2.8891)	(3.8054)
Nrent	0.3582	0.1584	0.3824
	(0.2612)	(0.2527)	(0.7209)
RTA	0.5043**	-0.2152	0.6597
	(0.2366)	(0.3211)	(0.4741)
BIT	1.6636***	0.1827	2.6188***
	(0.2196)	(0.3346)	(0.8081)
ODA (lagged)	-0.7329	0.0355	-0.8567
	(1.6744)	(1.0425)	(1.0202)
GHGP (lagged)	4.0808**	1.4511	13.9008**
	(1.8967)	(1.4682)	(6.5098)
GHGR (lagged)	-0.4702	-0.5996	0.0111
	(0.6669)	(0.6393)	(1.7426)
IQ	7.2855**	4.7431	26.0975*
	(3.1212)	(3.3389)	(14.6051)
Col	1.0051***	1.3194***	0.1782
	(0.2444)	(0.3341)	(0.6232)
DiploD (lagged)	1.4766*	1.0803**	4.4772**
	(0.7624)	(0.5521)	(1.7364)
Distcap	-0.9202***	-1.6174***	0.5862
	(0.3512)	(0.2557)	(0.5888)
Observations	16461	16461	16461
Pseudo R-squared	0.6741	0.6867	0.6556
Log pseudolikelihood	-11382283.31	-6600116.48	-3919632.089
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 15: Estimation for Small Islands countries

4.4.8 Estimation by considering climate finance through targeted objective: Climate Adaptation Finance and Climate Mitigation Finance

We assess our results by examining climate finance through targeted objectives: Climate Adaptation and climate Mtigation. Climate Adaptation Finance (CAF) aims to enhance a country's capacity to cope with the impacts of climate change, while Climate Mitigation Finance (CMF) provides financial support to reduce carbon emissions and foster greener economic growth. The findings for both adaptation finance (Table 16) and mitigation finance (Table 17) are consistent with the benchmark results. Vulnerable countries are not prioritized in the distribution of climate aid. Specifically, the coefficient for the vulnerability indicator (CV03) is negative and significant for total climate adaptation finance and loans-CAF, indicating that more vulnerable countries tend to receive less climate adaptation finance, particularly in the form of loans. Provider exports and trade agreements also seem to influence climate adaptation finance in a manner similar to the baseline results. Additionally, investment treaties (BIT), development aid (ODA), colonial relationships and institutional quality are positively associated with climate adaptation finance, particularly in the provision of grants. As with the baseline results, donor countries tend to allocate climate adaptation finance, especially grants, to countries that are geographically closer to them. Regarding climate mitigation finance, the vulnerability indicator is negative and not significant across all climate finance flows, suggesting that vulnerable countries are less likely to receive climate mitigation finance. Donor exports, trade agreements, investment treaties, and development aid positively influence the allocation of climate mitigation finance. Political proximity (DiploD) and geographical proximity (Distcap) also seem to contribute to the provision of climate mitigation finance. Another notable finding is that recipient countries with higher greenhouse gas emissions are not prioritized in the allocation of climate mitigation finance, which contrast with Halimanjaya (2015), who argued that climate mitigation finance tends to be allocated to countries with higher carbon emission intensity.

Variables	Total CAF	Grants-CAF	Loans-CAF
CV03 (lagged)	-28.8973**	-5.8208	-59.1561**
	(12.8292)	(6.9184)	(24.6363)
Exports (lagged)	0.2192***	0.2606***	0.2793**
	(0.0494)	(0.0366)	(0.1137)
GdpcR	0.0106	-0.4894	1.4582
	(0.5541)	(0.3473)	(1.2745)
GdpcP	-0.9921	-0.8053	5.7178*
	(0.8488)	(0.5453)	(3.4858)
Pop	0.3565	1.3525*	2.5987
	(0.9299)	(0.7818)	(2.0008)
Nrent	0.0582	0.3489***	-0.1463
	(0.1505)	(0.0941)	(0.2894)
RTA	0.6532***	0.0226	1.2051***
	(0.1718)	(0.1077)	(0.2575)
BIT	0.2354**	0.2801***	0.2011*
	(0.1049)	(0.0951)	(0.1582)
ODA (lagged)	1.0901*	1.5598***	0.6892*
	(0.6666)	(0.3898)	(0.3751)
GHGP (lagged)	1.0293	1.1172*	-3.3337
	(0.7782)	(0.6611)	(2.1194)
GHGR (lagged)	0.0034	0.1382	-0.3065
	(0.5926)	(0.2696)	(1.5981)
IQ	3.2652*	3.1493**	0.6694
	(2.1939)	(1.3837)	(4.6837)
Col	0.4652**	0.9989***	0.0435
	(0.1838)	(0.2085)	(0.3444)
DiploD (lagged)	-0.4318	-0.3581	-0.4195
	(0.4264)	(0.2764)	(0.8292)
Distcap	-0.4523***	-0.6611***	0.2514
	(0.1521)	(0.1079)	(0.2863)
Observations	79246	79246	79246
Pseudo R-squared	0.6518	0.6123	0.6481
Log pseudolikelihood	-140167667.6	-61153503.83	-76153701.48
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** $p<0.01$, significant at 1%, ** $p<0.05$, significant at 5%, * $p<0.1$ significant at 10%.

Table 16: Baseline estimation with Climate Adaptation Finance (CAF)

Variables	Total CMF	Grants-CMF	Loans-CMF
CV03 (lagged)	-5.4835	-6.6421	-12.9901
	(6.9864)	(6.72633)	(11.7507)
Exports (lagged)	0.2596***	0.2318***	0.4548***
	(0.0611)	(0.0473)	(0.1157)
GdpcR	-0.0301	-1.0387***	0.5211
	(0.6597)	(0.3657)	(1.0308)
GdpcP	2.7341*	0.8225	7.1301**
	(1.4491)	(0.5982)	(3.1061)
Pop	2.3117***	1.8947***	3.4344***
	(0.5424)	(0.4967)	(1.1777)
Nrent	0.1307	0.1301	0.1699
	(0.1199)	(0.0953)	(0.1741)
RTA	0.4783***	0.2078*	0.4908**
	(0.1638)	(0.1121)	(0.2326)
BIT	0.2257**	0.2502**	0.2519*
	(0.1112)	(0.0997)	(0.1467)
ODA (lagged)	1.5384***	2.5182***	1.2075***
	(0.3612)	(0.4473)	(0.2771)
GHGP (lagged)	-1.1142	-1.2625**	-2.5781
	(1.0361)	(0.6331)	(1.8502)
GHGR (lagged)	-1.4936***	-0.0633	-2.7177***
	(0.5748)	(0.4296)	(0.9043)
IQ	4.6158*	6.0445***	3.6805
	(2.6748)	(1.4545)	(3.6982)
Col	0.2196	0.9015***	-0.1042
	(0.2127)	(0.1696)	(0.4599)
DiploD (lagged)	-0.7572**	-0.7891***	-0.7397*
	(0.3832)	(0.2901)	(0.5459)
Distcap	-0.4569***	-0.3711***	-0.1619
	(0.1717)	(0.1227)	(0.3079)
Observations	79246	79246	79246
Pseudo R-squared	0.7269	0.5564	0.7348
Log pseudolikelihood	-238797339.3	-75463285.28	-157902134
Fixed and Year effects	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes

Standard errors in parentheses *** p<0.01, significant at 1%, ** p<0.05, significant at 5%, * p<0.1 significant at 10%.

Table 17: Baseline estimation with Climate Mitigation Finance (CMF)

5 Conclusion and Policy implications

This paper examined the challenge of climate change in relation to the determinants of international climate finance. Analyzing a sample of 140 recipient countries and 30 donor countries from 2000-2021 using a Gravity Panel Model, our findings indicate that countries highly vulnerable to climate change are less likely to receive climate finance, both in form of grants and loans. This suggests that vulnerable countries are not prioritized in international climate finance allocations. Additionally, self-interest factors such as economic and geopolitical considerations significantly influence bilateral climate finance, mirroring trends seen in development aid. Our results remain robust across various checks, including alternative model specifications and sub-sample analyses. Resource-rich countries, despite their vulnerability, also tend to receive less climate finance. This is noteworthy given their dual challenge of transitioning to sustainable energy and diversifying their economies, which could contribute to climate mitigation by reducing greenhouse gas emissions from resource extraction. For policy recommendations, we advise developed countries to focus more on vulnerable nations, particularly resource-rich ones. Since climate finance often favors countries with better institutional quality, we recommend that recipient countries work to enhance their institutional frameworks. Furthermore, given that bilateral climate aid is less likely to target the most vulnerable countries, we suggest that international institutions increase multilateral climate finance, with a focus on the most vulnerable nations. Additionally, we propose the establishment of an impartial international institution similar to the International Monetary Fund (IMF) or the World Bank, dedicated specifically to providing financial assistance to the countries most at risk from climate change.

Appendix

A List of recipient and provider countries

Table A1: Recipient countries

Afghanistan	Georgia	Pakistan
Albania	Ghana	Palau
Algeria	Grenada	Panama
Angola	Guatemala	Papua New Guinea
Antigua and Barbuda	Guinea	Paraguay
Argentina	Guinea-Bissau	Peru
Armenia	Guyana	Philippines
Azerbaijan	Haiti	Rwanda
Bangladesh	Honduras	Samoa
Barbados	India	Sao Tome and Principe
Belarus	Indonesia	Saudi Arabia
Belize	Iran, Islamic Rep.	Senegal
Benin	Iraq	Serbia
Bhutan	Jamaica	Seychelles
Bolivia	Jordan	Sierra Leone
Bosnia and Herzegovina	Kazakhstan	Solomon Islands
Botswana	Kenya	Somalia
Brazil	Korea, Dem. People's Rep.	South Africa
Burkina Faso	Kyrgyz Republic	Sri Lanka
Burundi	Lao PDR	St. Kitts and Nevis
Cabo Verde	Lebanon	St. Lucia
Cambodia	Lesotho	Sudan
Cameroon	Liberia	Suriname
Central African Republic	Libya	Syrian Arab Republic
Chad	Madagascar	Tajikistan
Chile	Malawi	Tanzania
China	Malaysia	Thailand
Colombia	Maldives	Timor-Leste

Continued on next page

Table A1 – *Continued from previous page*

Comoros	Mali	Togo
Congo, Dem. Rep.	Marshall Islands	Tonga
Congo, Rep.	Mauritania	Trinidad and Tobago
Costa Rica	Mauritius	Tunisia
Cote d'Ivoire	Mexico	Turkiye
Croatia	Micronesia, Fed. Sts.	Turkmenistan
Cuba	Moldova	Uganda
Djibouti	Mongolia	Ukraine
Dominica	Montenegro	Uruguay
Dominican Republic	Morocco	Uzbekistan
Ecuador	Mozambique	Vanuatu
Egypt, Arab Rep.	Myanmar	Venezuela, RB
El Salvador	Namibia	Vietnam
Equatorial Guinea	Nauru	Yemen, Rep.
Eritrea	Nepal	Zambia
Eswatini	Nicaragua	Zimbabwe
Ethiopia	Niger	
Fiji	Nigeria	
Gabon	North Macedonia	
Gambia, The	Oman	

Table A2: Provider countries by region

Europe	Asia	America	Oceania
Austria	Japan	Canada	Australia
Belgium	Korea, Rep.	United States	New Zealand
Czech Republic	United Arab Emirates		
Denmark			
Finland			
France			
Germany			
Greece			
Iceland			
Ireland			
Italy			
Lithuania			
Luxembourg			
Netherlands			
Norway			
Poland			
Portugal			
Slovak Republic			
Slovenia			
Spain			
Sweden			
Switzerland			
United Kingdom			

B The "CV03" indicator

Sectors	Indicators	Correlation with GDPC	Correlation p-value
Food	1. Projected change of cereal yields	-0.5387	0.0000
	2. Projected population change	-0.2755	0.0000
	3. Food import dependency	-0.3380	0.0000
	4. Rural population	-0.5870	0.0000
	5. Agriculture capacity	-0.4288	0.0000
	6. Child malnutrition	-0.4842	0.0000
Water	1. Projected change of annual runoff	0.0971	0.0000
	2. Projected change of annual groundwater recharge	-0.0538	0.0003
	3. Fresh water withdrawal rate	0.0621	0.0000
	4. Water dependency ratio	-0.0903	0.0000
	5. Dam capacity	-0.1103	0.0000
	6. Access to reliable drinking water	-0.6228	0.0000
Health	1.Projected change of deaths from climate induced diseases	-0.4225	0.0000
	2.Projected change in vector-borne disease	-0.1516	0.0000
	3. Dependency on external resources for health services	-0.3750	0.0000
	4. Slum population	-0.5868	0.0000
	5. Medical staff	-0.7179	0.0000
	6. Access to improved sanitation facilities	-0.6659	0.0000
Ecosystems	1. Projected change of biome distribution	0.0595	0.0001
	2. Projected change of marine biodiversity	0.2089	0.0000
	3. Natural capital dependency	-0.5505	0.0000
	4. Ecological footprint	0.4510	0.0000
	5. Projected biome	-0.5810	0.0000
	6. Engagement in international environmental conventions	-0.6019	0.0000
Habitat	1. Projected change of warm periods	-0.1350	0.0000
	2. Projected change of flood hazard	0.0736	0.0000
	3. Urban concentration	0.5870	0.0000
	4. Age dependency ratio	-0.4802	0.0000
	5. Quality of trade and transport infrastructure	-0.7903	0.0000
	6.Paved roads	-0.4658	0.0000
Infrastructure	1. Projected change of hydropower generation capacity	-0.1566	0.0000
	2. Projected change of sea level rise impacts	0.1870	0.0000
	3. Dependency on imported energy	0.2164	0.0000
	4. Population living under 5m above sea level	0.0979	0.0000
	5. Electricity access	-0.4317	0.0000
	6. Disaster preparedness	-0.4977	0.0000

Table B1: ND-GAIN Vulnerability sub-indicators and correlation values with GDPC

Sectors	Indicators	Correlation with GDPC
Food	2. Projected population change	-0.2755
Water	1. Projected change of annual runoff 2. Projected change of annual groundwater recharge 3. Fresh water withdrawal rate 4.Water dependency ratio 5.Dam capacity	0.0971 -0.0538 0.0621 -0.0903 -0.1103
Health	2.Projected change in vector-borne disease	-0.1516
Ecosystems	1. Projected change of biome distribution 2. Projected change of marine biodiversity	0.0595 0.2089
Habitat	1.Projected change of warm periods 2. Projected change of flood hazard	-0.1350 0.0736
Infrastructure	1. Projected change of hydropower generation capacity 2. Projected change of sea level rise impacts 3. Dependency on imported energy 4. Population living under 5m above sea level	-0.1566 0.1870 0.2164 0.0979

Table B2: sub-indicators used for CV03

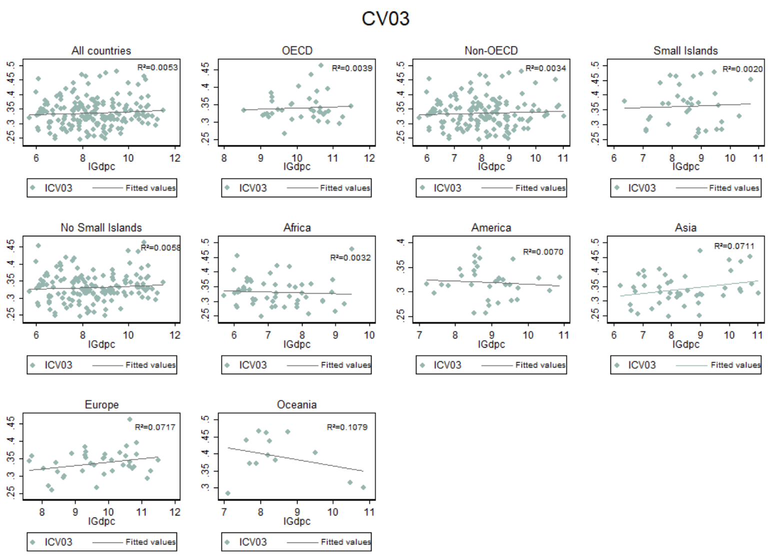

Figure B1: CV03 indicator and GDPC

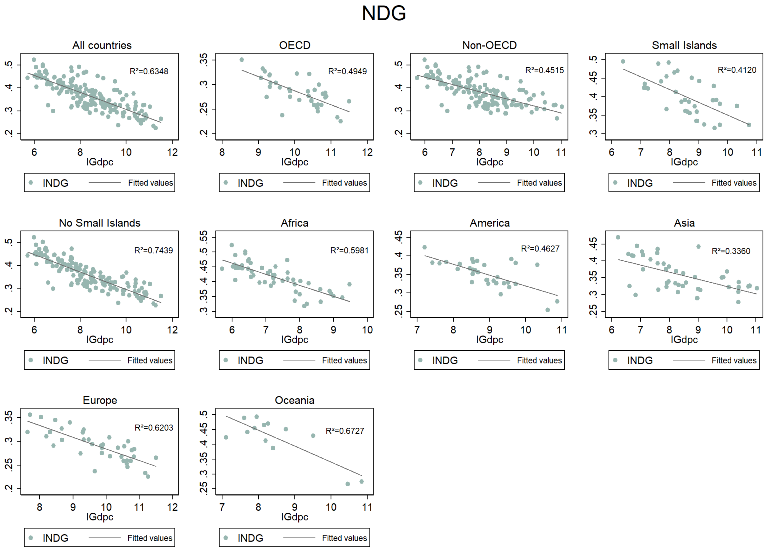

Figure B2: ND-GAIN indicator (NDG) and GDPC

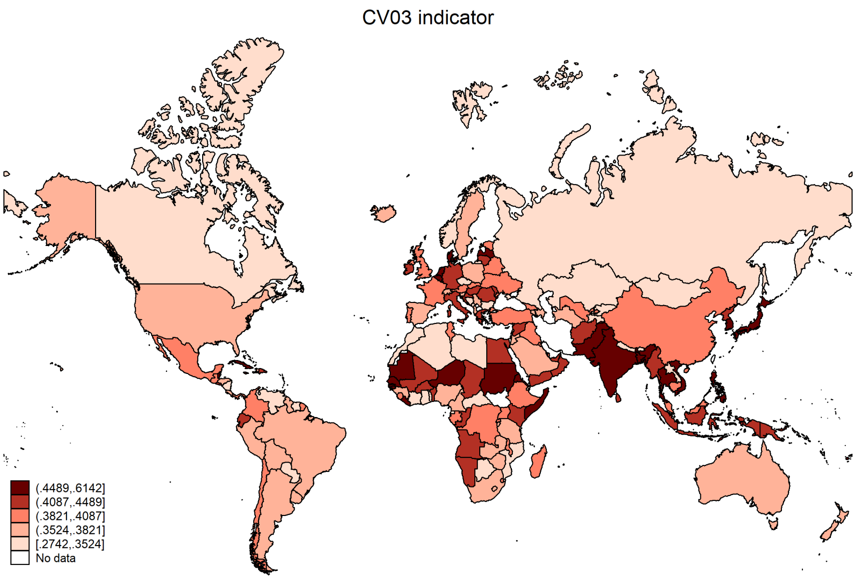

Figure B3: World map of countries's vulnerability level according to CV03 indicatior

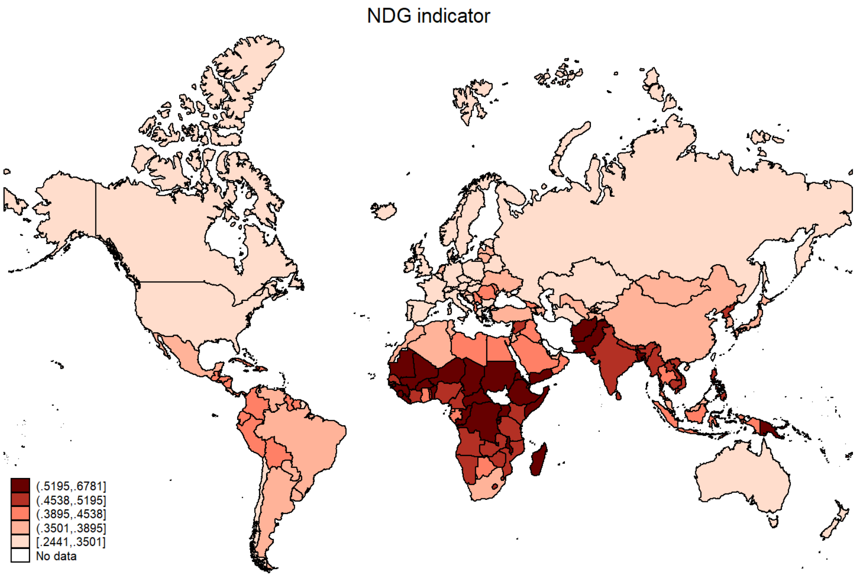

Figure B4: World map of countries's vulnerability level according to ND-GAIN indicator (NDG)

	NDG	CV04	CV03	CV02
GDPC	-0.03584***	-0.02081**	0.00814	0.00371
	(0.00756)	(0.01079)	(0.05423)	(0.00384)
NDisaster (Lagged)	0.00088	0.00336	0.00071	0.00052
	(0.00107)	(0.00459)	(0.00069)	(0.00053)
Temperature (Lagged)	0.0062	0.03764**	0.02404**	-0.01699
	(0.00877)	(0.01573)	(0.01177)	(0.08762)
Observations	4238	4238	4238	4238
Number of countries (including both developed and developing countries)	163	163	163	163
Log pseudolikelihood	-2731.7869	-2647.1453	-2690.3945	-2711.3204
Fixed and Year effects	Yes	Yes	Yes	Yes
Correction for heteroskedasticity	Yes	Yes	Yes	Yes

Standard errors in parentheses *** $p<0.01$, significant at 1%, ** $p<0.05$, significant at 5%, * $p<0.1$ significant at 10%.

Table B3: Fractional Response model estimation with ND-GAIN (NDG), CV03, CV04 and CV02 indicators.

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