Climate of Broken Promises: What Determines Recycled Climate Finance?

A quantitative research on country characteristics influencing the level of climate finance provided on top of development finance.

Name: Gwenyth Kenswiel

Student number: 496883

Word count: 11.994

Date of submission: 28-06-2024

First reader: Dr. M. Haverland

Second reader: Dr. C. Egger

International Public Management and Public Policy

Erasmus University Rotterdam

Abstract

At the 2009 Copenhagen Summit, developed countries pledged to collectively mobilise and provide 100 billion dollars annually by 2020 in new and additional climate finance to support developing nations in mitigating and adapting to climate change. Despite this commitment, many developed countries have failed to ensure that climate finance was truly 'new and additional' to their existing development support. This paper employs an ordered logit model to examine the country characteristics that influence nations' provision levels of new and additional climate finance. The analysis focuses on economic capability and political commitment determinants among 23 Annex-II Parties between 2011 and 2020. The results demonstrate that both economic capability and political commitment influence the level of new and additional climate finance provided by donor countries. Wealthier countries and those with high government debt and unemployment rates are less likely to provide the highest levels of new and additional climate finance. However, short-term economic growth does not significantly impact countries' provision levels. While public environmental concern does not translate into increased financial contributions, government environmental preferences appear to have a limited impact. Specifically, countries demonstrating stronger commitments to new and additional climate finance tend to participate in a greater number of IEAs. Although the composition of the cabinet does not influence climate finance contributions, countries with higher GHG emissions evolution levels tend to be larger contributors of new and additional climate finance. In addition, the largest current GHG emitters often shoulder a smaller share of the financial burden.

Keywords: Climate finance · New and additional · Official development aid · Country characteristics · Economic capability · Political commitment

Acknowledgements

First of all, I would like to express my sincere gratitude to Dr. Markus Haverland for supervising my thesis. I am deeply appreciative of the time you dedicated to repeatedly review my work and provide guidance and feedback at every stage of my thesis progress. Although your broad, open-ended questions caught me off guard at the beginning, they proved to be very helpful in the end. Your advice has helped me to navigate through the multitude of ideas and challenges that I have encountered throughout this process. I am particularly grateful for your encouragement to challenge myself with regard to the statistical analyses, given my lack of prior experience with STATA, fixed effects, and an ordered logit model. I believe that personal growth comes from embracing challenges, and you have helped me to do so. I would also like to thank my second reader, Dr. Clara Egger, for taking the time to review this thesis. Furthermore, I want to express my appreciation for the support of those in my personal sphere; thank you for being my pillars of mental support over the past six months. Finally, I would like to extend my sincere thanks to my peers in my thesis circle for their feedback during our meetings.

.

Table of Content

List of tables

List of figures

List of abbreviations

CBAM	Carbon Border Adjustment Mechanism
CBDR&RC	Common, But Differentiated, Responsibilities and Respective Capabilities
DAC	Development Assistance Committee
EU	European Union
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GNI	Gross National Income
IEA	International Environmental Agreement
IMF	International Monetary Fund
IPCC	Intergovernmental Panel on Climate Change
NCQG	New Collective Quantified Goal
ODA	Official Development Assistance
OECD	Organisation for Economic Co-Operation and Development
UN	United Nations
UNFCCC	United Nations Framework Convention on Climate Change
VIF	Variance Inflation Factor
WGI	Worldwide Governance Indicator

1. Introduction

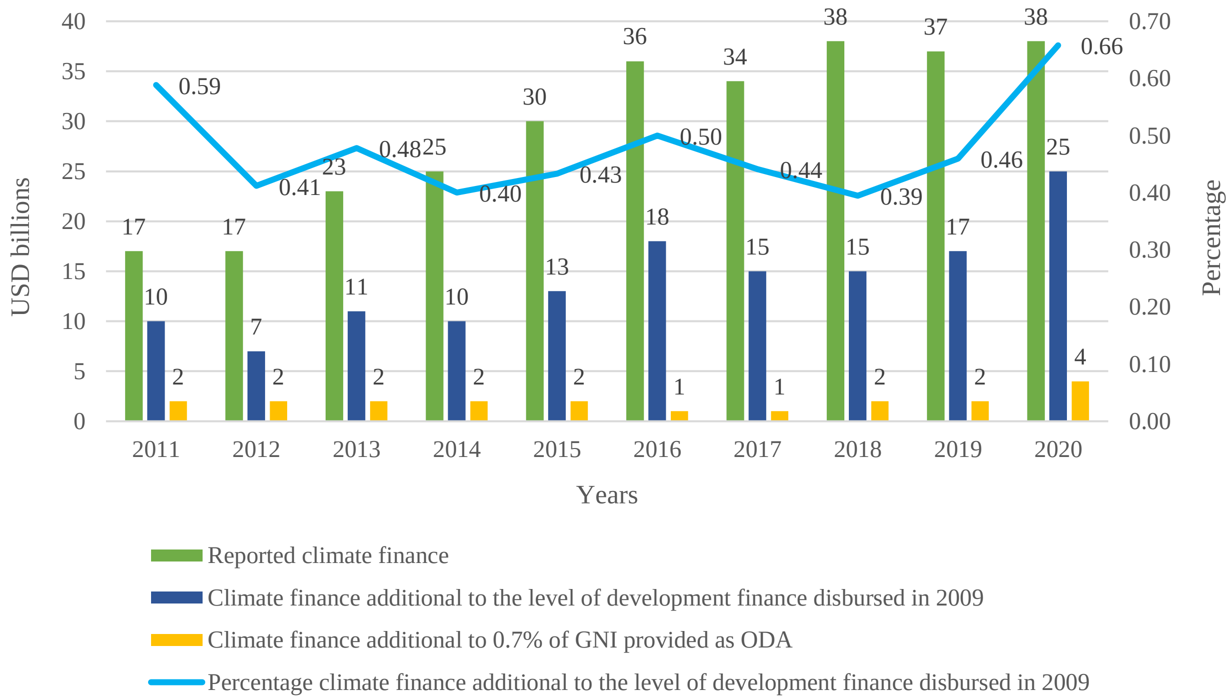
The 'promise' by developed countries to jointly mobilise and provide 100 billion dollars annually in climate finance to developing nations has finally been met, however, two years past the self-imposed deadline (Alayza et al., 2024; Harvey, 2023; OECD, 2024). This financial commitment, established during the 2009 United Nations Climate Conference in Copenhagen, is intended to support developing countries in their climate change adaptation and mitigation efforts by scaling up funding to 100 billion dollars annually from 2020 through 2025 (Halimanjaya, 2016; Kawabata, 2023; Weikmans, & Roberts, 2019). While this pledge represents less than 25 per cent of the yearly estimated climate finance needed by developing countries (Qian et al., 2023; Zhang, & Pan, 2016), concerns persist as these climate finance commitments are often met through the relabelling of existing development funds, rather than through providing 'new and additional' resources (Hattle et al., 2023; Miller et al., 2023; Mitchell et al., 2021). This has resulted in developing countries having to "pay twice for the costs of a changing climate" (Kenny, 2020a, p. 11): firstly, for bearing the disproportionate burden of climate change, and secondly, for the diversion of development finance flows towards climate finance (Kenny, 2020a, 2020b).

Climate finance is defined by the United Nations Framework Convention on Climate Change (UNFCCC) as "local, national, or transnational financing - drawn from public, private, and alternative sources of financing - that seeks to support mitigation and adaptation actions that will address climate change" (UNFCCC, n.d. a). The 1992 Convention on Climate Change stipulates that climate finance should be "new and additional" (UN, 1992, p. 13), which was reaffirmed in the Copenhagen Accord and the Cancun Agreement (UNFCCC, 2010, 2011). However, the concept 'new and additional' has not yet been formally defined due to lack of consensus among countries, resulting in varying interpretations regarding what qualifies as such (Pauw et al., 2022; Stadelmann et al., 2011). Nonetheless, it is widely understood that 'new and additional' climate finance refers to funding provided on top of conventional development assistance (Eyckmans et al., 2016), meaning that it is "not sourced or diverted from or double counted with other international financial streams" (Achampong, 2023, p. 72). Article 9 of the Paris Agreement confirms this interpretation by stating that the "mobilisation of climate finance should represent a progression beyond previous efforts" (UNFCCC, 2015, p. 13; Mitchell et al., 2021).

Developing countries argue that 'new and additional' climate finance should be supplementary to developed countries' commitment to provide 0.7 per cent of their gross national income (GNI) as official development assistance (ODA), while other nations interpret this less strictly, considering any increase above a predefined level – using 2009 development finance disbursements as a reference – to be additional, with climate finance included as part of their 0.7% GNI-commitment (Brown et al., 2010; Hattle et al., 2023; Michaelowa, & Namhata, 2022; UNCTAD, 2015). Irrespective of the interpretation chosen, the majority of the climate finance provided by developed countries has not met the 'new and additional' criteria (Hattle et al., 2023). As illustrated in Figure 1, out of the 295 billion dollars in public climate finance provided by Annex-II Parties between 2011 and 2020, only seven per cent was considered 'new and additional' to the 0.7% GNI-commitment, while 48 per cent exceeded the 2009 levels of development finance (Hattle et al., 2023). This indicates that more than half of the public climate finance has come from diverted development aid budgets (Hattle et al., 2023; Jensen, & Roniger, 2023).

Figure 1

Annual climate finance reported by Annex-II Parties from 2011 to 2020



Note. Adapted from "Seeing Double: Decoding the 'Additionality' of Climate Finance", by A. Hattle, J. Nordbo, A. Myrup, L. Elming, R.B. Sørensen, I. Achton, A.B. Knudsen, E. Bentsen, L.P. Nygaard, C. Mattson, and M. Hansen, 2023, p. 21.

Although there is an observed pattern of 'recycling' existing development funds to meet the 100 billion dollars pledge (Eklöf, 2022), the extent to which climate finance is diverted from these funds varies among countries, resulting in differences in the amount of 'new and additional' climate finance provided (Hattle et al., 2023; Jensen, & Roniger, 2023). This variation in funding is attributed by multiple studies to "discrepancies in the structures of global climate finance" (Qian at al., 2023, p. 43; Munira et al., 2021). Donor countries' failure to reach a formal agreement on their individual annual contributions (Timperley, 2021) means that contribution volumes of climate finance are decided upon domestically, leading to large variations in provision levels among developed countries (Klöck et al., 2018). The absence of binding commitments creates incentives for the under-provision of climate finance, consequently discouraging countries from providing 'new and additional' climate finance (Khan, & Munira; Michaelowa, & Namhata, 2022).

Beyond undefined contribution levels, prior research has emphasised the important role of recipient countries' characteristics in influencing donor's climate finance provision. Roberts et al. (2021) underscore that fragmented institutional architectures in recipient countries affect the transparency, accountability and effectiveness of climate finance (Ciplet et al., 2018; Weikmans, & Roberts, 2019), consequently reducing the willingness among donor countries to provide sufficient climate finance (Qian et al., 2023). However, according to Gilder and Rumble (2020), climate finance availability tends to be donor-centric rather than recipient-driven, with specific characteristics of donor countries influencing their provision levels. While all donors are developed countries, they vary greatly in terms of size, income level, economic structure, political regimes, environmental vulnerability, and international political power (Noel, 2023). Several of these features may affect their capacity and willingness to provide 'new and additional' climate finance.

Despite the calls and growing need for providing 'new and additional' resources, a substantial part of climate finance is sourced from development finance budgets (Hattle et al., 2023; Weikmans, & Roberts, 2019). So far, there have been no academic studies exploring the characteristics of donor countries that influence the provision of 'new and additional' climate finance. This paper addresses this academic literature gap by aiming to answer the following research question: "What country characteristics influenced nations' decisions to provide climate finance in excess of their 2009 development finance levels during the period from 2011 to 2020?"

This study empirically analyses donor countries' characteristics that potentially influence the provision of 'new and additional' climate finance, including economic capability and political commitment determinants, as detailed in the following sections. These determinants are regarded as key underlying factors affecting the ability and willingness of donor countries to provide climate finance (Klöck et al., 2018; Qian et al., 2023), but have not been previously studied in relation to the newness and additionality of climate finance provision. A panel dataset of 23 Annex-II Parties, the main donors of climate finance, is constructed and an ordered logit model is performed to examine the influence of different country characteristics.

This paper contributes to the academic discourse by identifying factors that influence both compliance with and deviation from the 'new and additional' climate finance commitment. While many countries fail to fully honour this pledge, systematic empirical evidence on the factors driving variations in contributions is lacking. Although previous research has touched upon political and economic factors in the broader context of climate finance provision (Klöck et al., 2018; Qian et al., 2023), the specific drivers that determine why certain countries fulfil their 'new and additional' climate finance promises while others do not remain largely unexplored. Hence, this study fills this gap by conducting a cross-country empirical analysis to identify the politico-economic country characteristics that influence variations in 'new and additional' climate finance provisions.

Beyond its academic significance, this study holds substantial societal relevance due to the escalating challenges posed by climate change. With an increasing number of countries and populations expected to be exposed to its impacts (IPCC, 2023), substantial financial support from developed countries is urgently needed to assist developing nations in their efforts to both adapt to and mitigate the effects of climate change. However, the political rather than needs-based commitment of 100 billion dollars (Alayza et al., 2024) falls drastically short of the estimated needs of developing countries and current contributions are even lower than expected (Qian et al., 2023; Zhang, & Pan, 2016). It is therefore crucial to understand why some countries are providing 'new and additional' climate finance, while others are not, especially in the light of the setting of a New Collective Quantified Goal (NCQG) at the upcoming COP29. This study contributes to societal relevance by identifying the underlying factors of this discrepancy, thereby facilitating the identification of appropriate solutions (Qian et al., 2023).

The remainder of the study is structured as follows. In Section 2, a literature review is presented summarising prior empirical studies on country characteristics influencing climate finance provision, while also noting the novelty of this study. Section 3 outlines the methodology and data used to answer the research question. The findings of the empirical analysis are presented and interpreted in Section 4. Section 5 discusses the conclusion and discussion. Lastly, in Section 6 recommendations for policy implications are formulated.

2. Theoretical framework

The present section provides an overview of the literature on climate finance and climate aid. It discusses donor country characteristics that influence variations in the provision of climate finance, focusing specifically on differences in economic capability and political commitment.

2.1 Climate finance provision

A small strand of the academic and grey literature examines the variation in climate finance provision. They analyse climate finance, in particular climate aid, reported by donor countries and assess the determinants of their provision. Their findings are presented in Subsection 2.1.1 and 2.1.2. Based on these observations, five hypotheses are proposed to explain donor countries' behaviour in providing new and additional climate finance.

2.1.1 Economic capability in climate finance provision

The capability of a country to provide additional financial support to other nations is generally considered to be based on its level of economic wealth (Klöck et al., 2018; Qian et al., 2023). According to the Common, but Differentiated, Responsibilities and Respective Capabilities (CBDR&RC) principle of the UNFCCC, countries with greater financial capacity are expected to contribute a larger share in climate finance (Qi, & Qian, 2023), as they are presumed to be better able to provide supplementary financing (Halimanjaya, & Papyrakis, 2015). Nevertheless, global climate finance constitutes about one per cent of the global GDP (Buchner et al., 2023). Klöck et al. (2018) find that countries with a higher GDP per capita tend to provide more climate aid. This observation is in line with the findings of Li and Reuveny (2006), who demonstrate that global carbon abatement efforts increase as income rises, indicating a correlation between income levels and the financial ability to support such efforts. In contrast, Halimanjaya and Papyrakis (2015) do not observe a significant correlation between donor countries' level of mitigation finance, as part of their total ODA, and their GDP per capita level. This suggests that while richer countries may provide larger sums of overall ODA, they do not necessarily allocate a greater proportion of their ODA towards mitigation finance. This could be because they prioritise other types of aid that have stronger impacts on local development (Halimanjaya, & Papyrakis, 2015). Qian et al. (2023) further find that the provision of climate finance is not influenced by donor countries' short-term economic disturbances, as indicated by GDP growth, but rather by their long-term economic development level. In addition, Hicks et al. (2008) find that wealthier donor countries, measured by GDP per capita, tend to provide more aid towards green projects, which have global environmental benefits, and less aid to brown projects, which deliver localised environmental benefits. This suggests that richer countries prioritise addressing broader environmental challenges over specific needs of environmental aid recipients (Hicks et al., 2008). Furthermore, Noel et al. (2023) investigated climate aid projects and conclude that GDP per capita and GDP growth are negatively associated with the probability of project over-coding, implying that richer donor countries are less prone to over-code existing development aid projects as climate-related.

Drawing upon these findings in the literature, the inverse relationship between economic wealth and over-coding suggests that poorer nations are less likely to increase their climate contributions, as over-coding indirectly implies that reported contributions are not new or additional (Noel et al., 2023). This indicates that wealthier countries are more committed to providing new and additional climate contributions. Consequently, it can be inferred that economic capacity influences the extent of new and additional climate finance provided by donor countries. This understanding leads to the formulation of the first hypothesis:

> **H_1.** *Donor countries with more economic capacity are more likely to provide new and additional climate finance.*

Economic capacity beyond GDP level may also affect donor countries' provision of climate aid. Aid efforts tend to fluctuate in response to macroeconomic conditions within the donor country (Fuchs et al., 2014). Fuchs et al. (2014) find that donor governments' debt decreases their aid efforts. When government debts are high, domestic spending priorities might shift, replacing foreign aid with an increased focus on internal needs (Fuchs et al., 2014). This aligns with research by Halimanjaya and Papyrakis (2015), who demonstrate a negative correlation between donor countries' domestic environmental spending and the share of ODA committed to climate mitigation finance. Similarly, Hicks et al. (2008) indicate that increased domestic spending on environmental projects decreases the funding available for international environmental activities. In addition, while Noel et al. (2023) do not find government debt to be a significant factor influencing climate aid project over-reporting tendencies, they do find an association between higher unemployment rates and an increased probability of projects being over-coded as climate-related.

Based on these findings, it is expected that the provision of climate finance decreases during periods of deteriorating macroeconomic conditions in the donor country. While research suggests that government debt is not significantly correlated with over-coding (Noel et al., 2023), and thus indirectly with new and additional climate contributions, it is reasonable to expect that countries burdened with high levels of government debt might provide less new and additional climate finance. This is because high debt levels limit a country's ability to allocate funds to international climate initiatives, as resources are often directed towards debt repayment (Hicks et al., 2008). Furthermore, during periods of high unemployment, environmental concerns may become less of a priority as people focus more on immediate economic issues (Michaelowa, & Michaelowa, 2011). This implies that governments may feel less compelled to provide new and additional climate finance when unemployment rates are high. Consequently, high government debts and unemployment rates appear to influence the amount of new and additional climate finance provided by donor countries, leading to the following hypothesis:

H_2. *Donor countries with tighter fiscal constraints are less likely to provide new and additional climate finance.*

2.1.2 Political commitment to climate finance provision

Domestic political concerns also contribute to the level of generosity in countries' climate finance efforts (Klöck et al., 2018). Michaelowa and Michaelowa (2011) find that donor governments' ideological orientation as well as national voter's environmental preferences influence the over-coding of aid projects as climate-related. While left-leaning governments tend to decrease over-coding, ecological preferences among voters often lead to increased over-coding (Michaelowa, & Michaelowa, 2011). Similar findings are reported by Noel et al. (2023), who indicate that donor governments with a more environmentally-concerned population tend to over-report development aid as climate-related as part of their electoral strategy. However, these electoral motivations behind over-coding are only observed in less wealthy donor countries, which often face more stringent budget constraints. Additionally, Noel et al. (2023) find that donor countries with stronger environmental preferences, indicated by reduced greenhouse gas (GHG) emissions since the Kyoto Protocol and a greater number of International Environmental Agreements (IEAs) in force, are less likely to over-report aid projects as climate-related. In contrast, more climate-related laws and policies and higher values of the Protected Areas Representativeness Index are significantly correlated with increased over-reporting. However, the authors argue that these correlations likely stem from the shortcomings of the measurement method, which only provides a rough estimation of a country's climate policy stringency (Noel et al., 2023).

Despite these findings regarding over-reporting, the relationship between domestic political ideology and the provision of climate finance remains inconclusive in the existing literature (Qian et al., 2023; Qi, & Qian, 2023). Neumayer (2004) and Carter (2013) argue that left-wing parties tend to have more pro-environmental stances than their right-wing counterparts, although this difference is often marginal. However, this stronger environmental orientation does not necessarily translate into greater altruism in the provision of foreign (environmental) aid by left-wing governments (Fuchs et al., 2014; Greene, & Licht, 2018). Likewise, Greene and Licht (2018) find that a right-wing political ideology rarely leads to a reduction in foreign aid, even when coupled with anti-internationalism. However, Klöck et al. (2018) find that donor countries which are more concerned about climate change, as measured by the share of representatives of green parties in parliament, tend to provide less climate aid. This implies that the higher the representation of green parties in parliament, the less climate aid a country provides. This inverse relationship is presumably because green parties are often in opposition (Klöck et al., 2018). Furthermore, Klöck et al. (2018) observe that the presence of an environmentally-concerned population does not significantly influence climate aid provision. However, this absence of correlation may stem from their operationalisation, as they define an environmentally-concerned population as individuals with tertiary education rather than considering the share of green party votes in parliamentary elections, as other research has done (Noel et al., 2023). They justify this operationalisation by arguing that higher levels of education often correlate with greater environmental concerns and awareness of climate change (Klöck et al., 2018).

In contrast to Klöck et al.'s (2018) findings, Halimanjaya and Papyrakis (2015) identify a negative, weak and statistically non-significant correlation between the political orientation of donor governments, measured using a left-right government orientation index, and their commitment to climate mitigation. Additionally, Qian et al. (2023) find that prior to the Paris Agreement, the presence of more green party seats or left party's governance had no significant influence on donor countries' provision of climate aid. However, after the Paris Agreement, a greater number of green party seats is associated with a higher provision of climate aid, although this correlation is very weak. This aligns with Hicks et al.'s (2008) finding that left governing party seats in donor governments has little impact on green aid allocation decisions.

Existing literature suggests that public ecological preferences are positively correlated with the over-coding of aid projects as climate-related (Michaelowa, & Michaelowa, 2011; Noel et al., 2023). However, this relationship is not expected to extend to the provision of new and additional climate finance. While over-coding implies that reported contributions are not truly new or additional, it focuses on the relabelling of projects as climate-related rather than the provision of extra climate finance. Voters with strong environmental preferences are presumed to not only value climate-related aid, but also to scrutinise government environmental policies more closely, therefore posing an electoral risk for governments that fail to provide new and additional climate finance (Michaelowa, & Michaelowa, 2011; Noel et al., 2023). Although it is difficult to detect whether reported statistics represent new and additional climate finance (Michaelowa, & Michaelowa, 2011), it is anticipated that electoral pressure will incentive the provision of such finance. Based on this expectation, the following hypothesis is formulated:

> **H3.** *Donor governments with a larger environmentally-concerned population are more likely to provide new and additional climate finance.*

While the direction of the relationship between domestic political orientation and climate aid provision cannot be definitively determined on theoretical grounds, it is expected that governments with stronger environmental preferences will be more inclined to provide new and additional climate finance. This expectation is based on research indicating that such governments tend to over-code their climate aid projects less frequently (Michaelowa, & Michaelowa, 2011; Noel et al., 2023), implying a stronger commitment to providing additional climate contributions. When a government has a strong environmental focus, increasing the provision of new and additional climate finance leads to higher utility, even if it entails reducing spending in other areas that are equally valued by the public. Consequently, under certain levels of public environmental support, governments with strong environmental preferences will provide more genuinely new and additional climate finance (Michaelowa, & Michaelowa, 2011). This will narrow the gap between merely relabelling development finance as climate finance and actually providing new funding, resulting in an increase in the provision of new and additional climate finance. This expectation leads to the fourth hypothesis:

> **H4.** *Donor governments with stronger environmental preferences are more likely to provide new and additional climate finance.*

Beyond domestic political considerations, the perceived political responsibility of donor countries also influences climate finance generosity. According to the CBDR&RC principle, countries historically emitting high levels of GHGs bear a greater responsibility to finance climate change mitigation and adaptation efforts (Klöck et al., 2018; Tan, 2023). This principle emphasises that polluters should pay more, suggesting that “those countries most responsible for climate change (...) [should] also contribute most to the joint climate aid target” (Klöck et al., 2018, p. 902; Corvino, 2023). However, Klöck et al. (2018) find that countries with the lowest contributions to global CO_2 emissions, both in total and per capita, tend to provide the highest levels of climate aid, indicating a reverse relationship between GHG emissions and financial contributions. This finding is supported by Noel et al. (2023), who demonstrate that donor countries whose GHG emissions have increased since the Kyoto Protocol tend to over-report their aid as climate-related. In contrast, Halimanjaya and Papyrakis (2015) do not find a statistically significant correlation between CO_2 emissions per capita and mitigation finance commitments. This implies that donor countries’ levels of per capita CO_2 emissions do not significantly influence their commitments to mitigation financial support, even though these countries might still commit larger amounts of overall ODA (Halimanjaya, & Papyrakis, 2015).

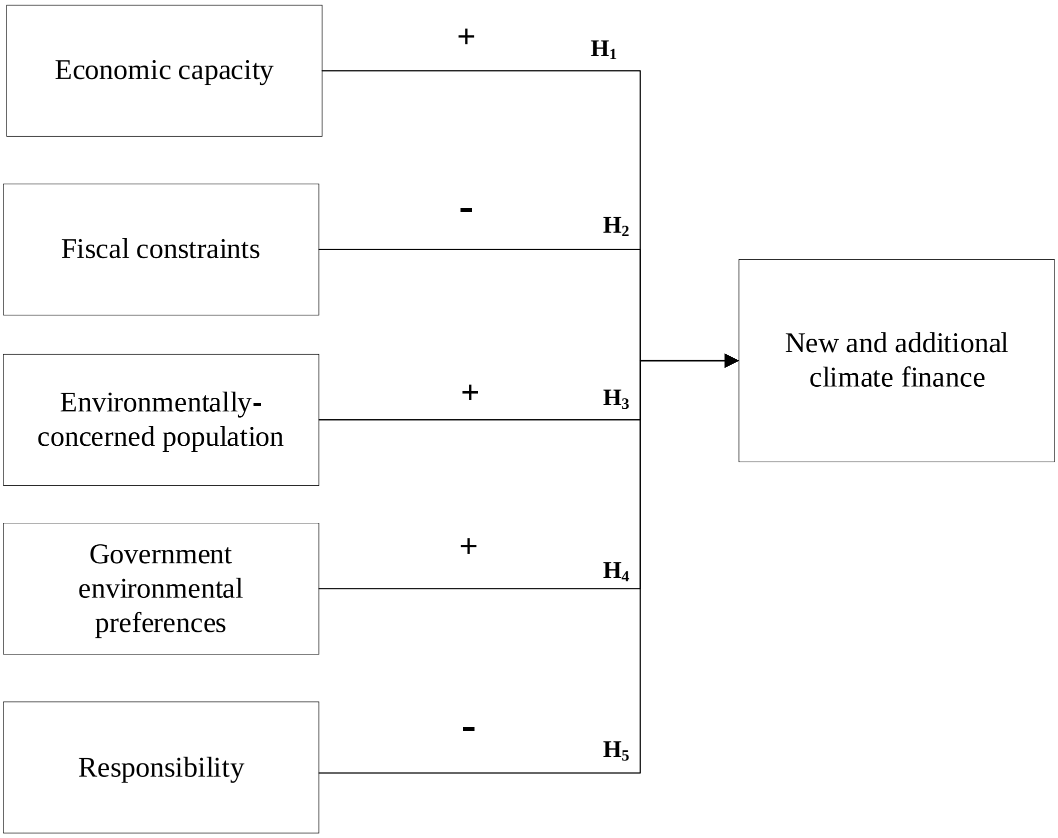
Expanding on these findings, the correlation between increased post-Kyoto GHG emissions and over-coding suggests that donor countries with rising GHG emissions are less inclined to increase their climate contributions (Noel et al., 2023). This indirectly implies that countries that have reduced their GHG emissions from their Kyoto Protocol levels are more likely to provide new and additional climate contributions. It can therefore be expected that responsibility influences the amount of new and additional climate finance provided by donor countries. This understanding leads to the fifth hypothesis:

> **H_5.** *Donor countries that bear greater responsibility for climate change are less likely to provide new and additional climate finance.*

The expected relationships between the concepts, as outlined in the hypotheses, are illustrated in the conceptual model in Figure 2.

Figure 2

Conceptual model



3. Research design

This study adopts a deductive quantitative approach to examine the influence of donor country characteristics on the provision of new and additional climate finance. A cross-country empirical analysis is conducted, using data from 23 Annex-II Parties between 2011 and 2020, by employing an ordered logit model. Data was sourced from existing databases and analysed using the statistical software STATA, version 18.

This section outlines the research design and methodological justification. Subsection 3.1 presents the operationalisation of the variables, followed by Subsection 3.2 through 3.4, which detail the empirical strategy. Subsection 3.5 subsequently discusses the potential limitations and ethical considerations of the study.

3.1 Operationalisation

In the following section, the dependent, independent, and control variables are operationalised. This includes new and additional climate finance as the dependent variable, country characteristics related to economic capability and political commitment as independent variables, and additional control variables.

3.1.1 Dependent variable

The dependent variable in this study is represented by the percentage of new and additional climate finance per donor country per year (see Appendices A and B). This is measured based on data obtained from the OECD DAC dataset and Biennial Reports under the UNFCCC (Hattle et al., 2023), which both exclusively rely on donors' subjective classification of their aid and finance as climate-related (Weikmans, & Roberts, 2019).

The dependent variable 'new and additional climate finance' is operationalised according to the definition of Hattle et al. (2023), which defines it as "the amount of climate finance which has been provided by wealthy countries [Annex-II Parties] on top of the level of development finance they contributed in 2009, the year of the COP15 climate finance commitment" (p. 16). This definition is chosen, because the majority of donor countries have not provided climate finance in excess to the 0.7% GNI-commitment between 2011 and 2020 (Hattle et al., 2023). To construct this variable, the OECD DAC dataset is used to determine each Party's total provision of ODA and other official flows (OOF) through bilateral and multilateral channels in 2009, serving as the baseline of development finance disbursed by each country in 2009 (Hattle et al., 2023; OECD, n.d.). Additionally, the climate finance reported by each Party to the UNFCCC as bilateral and multilateral ODA and OOF during the period from 2011 to 2020 is gathered from the first through fifth Biennial Reports of Annex-II Parties (Hattle et al., 2023; UNFCCC, n.d. b). This reported climate finance for each respective year is then compared to the amount of climate finance that exceeded the level of development finance provided in 2009 for the corresponding year. This excess amount, which represents the new and additional climate finance provided, is identified by Hattle et al. (2023). The resulting ratio indicates the proportion of new and additional climate finance. An increase in a country's development finance contribution, relative to the baseline of 2009, sets the threshold for new and additional climate finance. Conversely, if a Party's annual provision of development finance has either stagnated or decreased compared to 2009, climate finance cannot be considered new and additional (Hattle et al., 2023).

In line with Hattle et al. (2023), this study considers both concessional ODA and non-concessional finance reported as OOF as qualifying for new and additional climate finance. Despite the fact that non-concessional finance is often provided on less favourable terms, such as loans, adding to public budgets and debt burdens in the global South (Shishlov, & Censkowsky, 2022; Zagema et al., 2023), both concessional and non-concessional funding instruments are recognised as legitimate sources for meeting climate finance obligations (Hattle et al., 2023; Zagema et al., 2023).

Due to the presence of a large number of zeros (see Appendix B), the continuous dependent variable is transformed into a four-category ordinal variable, reflecting the percentage range in which a donor country falls in terms of new and additional climate finance provision (Green, 2021). These categories are labelled as: ‘zero’, ‘weak’, ‘moderate’, and ‘strong’. To ensure that all zero values fell into the same category, quantiles were used instead of quartiles (Field, 2013). The quantile boundary separating the second and third categories was manually adjusted to create categories that cover equal ranges of the data. This resulted in the following categorisation: Category 1 (zero) denotes that a country did not provide any new and additional climate finance. Category 2 (weak) includes cases where the value of new and additional climate finance provision is between 0.0019 and 0.4167. In Category 3 (moderate), the new and additional climate finance value ranges from 0.422 to 0.8466. Finally, Category 4 (strong) encompasses instances where the value of new and additional climate finance is between 0.8548 and 1, indicating a notably high level of new and additional climate finance provision.

3.1.2 Independent variables

Economic capability

A country’s capability to make annual contributions to the 2009 climate finance commitment is best assessed by its level of economic wealth and prosperity (Klöck et al., 2018; Qian et al., 2023). Economic capability is examined by economic capacity and fiscal constraints (Noel et al., 2023; Qian et al., 2023). Firstly, a donor country’s economic capacity is measured by GDP per capita and GDP growth, aligning with Klöck et al. (2018) and Qian et al. (2023). GDP per capita is obtained from the World Bank Open Data catalogue, expressed in USD and corrected for inflation by using GDP in constant 2015 price (World Bank, n.d. a). Similarly, the GDP growth rate, expressed in percentage, is retrieved from the World Bank Open Data catalogue (World Bank, n.d. b), serving as an indicator of the economy's overall health and reflecting its short-term fluctuations (Qian et al., 2023). Secondly, in line with Noel et al. (2023), fiscal constraint is measured by countries' government debt and unemployment rate. General government gross debt as a percentage of GDP is sourced from the International Monetary Fund (IMF) database (IMF, n.d.). High levels of government debt can constrain a country's financial capability to support other countries (Fuchs et al., 2014). In addition, unemployment rate, depicted as a percentage of civilian labour force, is derived from the Comparative Political Dataset compiled by Armingeon et al. (2023). This ratio is expected to reflect a donor's behaviour in response to a deteriorating economic situation (Noel et al., 2023).

Political commitment

Three concepts are used to quantify countries' political commitment: environmentally-concerned population, government environmental preferences, and donor responsibility. These indicators are drawn from research of Klöck et al. (2018), Michaelowa, & Michaelowa (2011), Noel et al. (2023), and Qian et al. (2023). Firstly, the level of concern for environmental issues within the donor population is measured by the share of green party votes in parliamentary elections. This is calculated based on data from the Comparative Political Data Set (Armingeon et al., 2023), following the methodology employed by Michaelowa and Michaelowa (2011), Bodenstein and Kemmerling (2015), and Noel et al. (2023). Secondly, government environmental preferences are assessed through three indicators. The first indicator is the cabinet composition, measured using the Schmidt index, which is derived from the Comparative Political Data Set (Armingeon et al., 2023; Michaelowa, & Michaelowa, 2011). The index ranges from 1 (hegemony of right-wing and centre parties) to 5 (hegemony of social-democratic and other left parties). The overall political orientation of the cabinet is expected to reflect the government's stance on foreign environmental aid, as left-wing governments are less likely to over-code aid projects as climate-related (Michaelowa, & Michaelowa, 2011). In addition, the remaining indicators are related to environmental policy stringency, aligning with Noel et al. (2023). The second indicator involves the relative evolution of national GHG emissions (excluding land use, land use change, and forestry) since the Kyoto Protocol, as 1990 serves as the base year for the national GHG inventory of all Parties in this dataset (UNFCCC, 2008). This percentage is computed from the UNFCCC GHG Database (UNFCCC, n.d. c). The third indicator concerns the number of IEAs in force, extracted from the IEA Database Project (Mitchell, 2022). Thirdly, a country's responsibility for climate change is assessed by considering two measures of countries' GHG emissions, in line with the research of Klöck et al. (2018). First, annual GHG emissions per capita are used, "which allows for country comparisons independent of country size" (Klöck et al., 2018, p. 901). This indicator is sourced from the World Bank Open Data catalogue and is expressed in metric tons (World Bank, n.d. c). Second, recognising that smaller countries, despite possibly having high per capita GHG emissions, may carry less weight in global GHG emissions discussions and therefore receive less international scrutiny, a measure of countries' annual emissions is included (Klöck et al., 2018). This is expressed in kiloton of CO_2 equivalent and retrieved from the UNFCCC GHG Database (UNFCCC, n.d. c). However, due to multicollinearity issues, only the first measure, GHG emissions per capita, is utilised in the analysis (Field, 2013; Meuleman et al., 2015).

3.1.3 Control variables

Control variables are included to account for potential intervening factors that could influence the relationship between new and additional climate finance and country characteristics.

Firstly, total amount of annual development aid is controlled for, as prior studies have demonstrated a significant and positive correlation between total development aid and climate finance (Klöck et al., 2018; Qian et al., 2023). This data is sourced from the OECD DAC database and expressed in USD millions (OECD, n.d.). It is important to note that climate finance is a subset of total development aid. While this could raise endogeneity concerns due to correlated factors influencing both funding decisions (Brüderl, & Ludwig, 2015), the focus on the share of new and additional climate finance mitigates some of these concerns compared to analysing total investment amounts.

Secondly, countries' institutional quality is considered, as several studies have found a positive relationship between institutional quality and climate aid provision (Halimanjaya, & Papyrakis, 2015; Michaelowa, & Michaelowa 2011; Noel et al., 2023). The six Worldwide Governance Indicators (WGIs) of the World Bank are used to measure donor countries' institutional quality. These indicators include: voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, the rule of law, and control of corruption (Kaufmann, & Kraay, 2023). The indicators' data is sourced from Kaufmann and Kraay's (2023) WGI dataset. Each index ranges from approximately -2.5 to 2.5, with higher values indicating better governance. Given the strong correlations between these indicators (see Appendix C, Table 5), an average institutional quality score is created by computing the mean of these six WGIs to avoid multicollinearity (Halimanjaya, & Papyrakis, 2015; Noel et al., 2023).

Thirdly, direct vulnerability to climate change is accounted for. Vulnerability is associated with less climate aid provision, possibly because vulnerable countries prioritise domestic spending over international aid (Klöck et al., 2018). In line with Klöck et al. (2018) and Noel et al. (2023), the Notre Dame Global Adaptation Index is used to measure the direct effects of climate change (ND-GAIN, 2023). As the index incorporates both measures of vulnerability and readiness, focus is placed on one specific sub-measure: the ND-GAIN vulnerability index. This index assesses a country's overall vulnerability to the negative impacts of climate change by considering its exposure, sensitivity, and adaptive capacity in six life-supporting sectors, including food, water, health, ecosystem services, human habitat, and infrastructure (ND-GAIN, 2023). The vulnerability score, calculated as the mean of the sector scores, ranges from 0 to 1, with higher values corresponding to greater vulnerability to climate change impacts (ND-GAIN, 2023).

3.2 Country and year sample

The analysis focuses on data from 23 donor countries spanning the period from 2011 to 2020. These countries are all classified as Annex-II Parties, obligated to provide new and additional climate finance to developing countries (UNFCCC, n.d. d). Climate finance contributions from the European Union, which is also an Annex-II Party, are excluded as donor countries' characteristics are considered. The decision to include all Annex-II Party countries in the sample was made to enhance the external validity of this study. The research timeframe covers the years 2011 to 2020, aligning with the commitment made by developed countries in 2009 to support climate change adaptation and mitigation activities in developing nations. This commitment includes the pledge of "scaled-up, new and additional finance, reaching USD 100 billion" annually by 2020 (Hattle et al., 2023, p. 4). The year 2010 is excluded from the analysis due to the absence of reported climate finance totals to the UNFCCC for that year (Hattle et al., 2023).

3.3 Model selection

Given the skewed distribution and the large proportion of zeros in the dependent variable, alongside the panel nature of the data, three econometric models were tested to determine the most appropriate model for the data.

Firstly, fixed-effects and random-effects models were considered. These models are particularly suitable for panel data, as they address the omitted variable bias by controlling for unobserved heterogeneity (Brüderl, & Ludwig, 2015). To determine the preferable model, the Durbin-Wu-Hausman test was performed (Fortin-Rittberger, 2015). The rejection of the null hypothesis ($Chi^2 = 54.51$; $p < .01$), which indicates that the difference in the coefficients is not systematic, suggested that a fixed-effects model would be more appropriate (see Appendix D, Table 6). However, the heavily skewness of the dependent variable, attributed to the prevalence of zeros and ones, violated the normal distribution assumption (see Appendix D, Figure 3; Boulton, & Williford, 2018; Green, 2021). Consequently, alternative models better suited for this type of data were explored.

Subsequently, due to the substantial number of zeros in the dependent variable, the variable was transformed into a binary variable, indicating whether a donor country provided new and additional climate finance (Green, 2021). This binary variable was categorised as follows: 0 denotes that a country did not provide new and additional climate finance, while 1 indicates that a country provided new and additional climate finance. A binary logit model, with and without fixed-effects, was then conducted to analyse the effect of country characteristics on the provision of new and additional climate finance. Although the model effectively accounted for zero inflation (Green, 2021) and produced statistically significant results (see Appendix D, Table 7), it oversimplified the data due to the dichotomous nature of the dependent variable. This oversimplification resulted in the loss of valuable nuances, as any contribution of new and additional climate finance greater than zero per cent was included in the 1-category.

Finally, an ordered logit model was employed, which categorises the continuous variable into ordered groups. This model is particularly suitable, as it enables the large number of zeros in the dependent variable to be categorised into the lowest category of an ordered scale (Boulton, & Williford, 2018). Unlike the binary logit model, the ordered logit approach allows the dependent variable to encompass a range of values, thereby preserving more information and capturing gradations in new and additional climate finance provisions. However, compared to the fixed-effects model, a disadvantage of this model is the loss of information that occurs when a continuous variable is categorised. Nevertheless, the ordered logit model was selected because the fixed-effects model was less suitable (Boulton, & Williford, 2018). Furthermore, given the panel nature of the data, year and country fixed-effects were included in the model to account for unobserved heterogeneity and to check the robustness of the findings (Brüderl, & Ludwig, 2015).

3.4 Model specification

In this study, an ordered logit model is used to examine the relationship between new and additional climate finance provision and donor countries' characteristics. The model is represented as follows (Best, & Wolf, 2015; Long, 2015):

$$y_i^* = x_i'\beta + \varepsilon_i \tag{1}$$

Where y^* is an unobserved variable, representing a value on a latent continuum. The value of this latent variable is only known when it crosses certain thresholds. In this equation, y_i^* denotes the dependent variable, the percentage new and additional climate finance, for the *i*-th observation. The vector x represents the set of independent variables explaining y^*, with associated regression coefficients β. This linear combination of regressors and coefficients is expressed as: $x'\beta = \beta_1 x_1 + \cdots + \beta_j x_j$. The term ε represents the error term, which is assumed to have a logistic distribution (Grilli, & Rampichini, 2014; Long, 2015).

The latent variable y^* is divided into observable ordinal categories using the thresholds $\tau_0, \ldots, \tau_j$. The subsequent rule links the latent variable y_i^* to the observed ordered variable y_i through the thresholds τ_j (Baetschmann et al., 2020; Long, 2015):

$$y_i = j \ \text{ if } \ \tau_{j-1} < y_i^* \leq \tau_j \ \text{ for } j = 1, \ldots, J \tag{2}$$

Where $\tau_0 = -\infty$ and $\tau_j = \infty$. However, considering that the dependent variable represents the percentage of new and additional climate finance, constrained within the range of 0 to 100, the thresholds are adjusted to $\tau_0 = 0$ and $\tau_j = 100$.

For new and additional climate finance, the observed categories of y^* are determined by the following measurement model (Long, 2015; Wang, & Kockelman, 2005):

$$y_i = \begin{cases} 1 & if\ y_i^* \leq \tau_0 = 0 \\ 2 & if\ \tau_0 < y_i^* \leq \tau_1 \\ 3 & if\ \tau_1 < y_i^* \leq \tau_2 \\ 4 & if\ \tau_2 < y_i^* \leq \tau_3 = 100 \end{cases} \tag{3}$$

Where the observed variable y_i takes the value 2 if y_i^* exceeds threshold value τ_0 and is less than or equal to threshold value τ_1 (Best, & Wolf, 2015). Since ε is assumed to follow a logistic distribution, the probability of a country's new and additional climate finance provision being equal to category *j* can be computed as (Liu, 2009; Long, 2015):

$$\begin{aligned} \mathrm{P}(y_i = j \mid x_i) &= \mathrm{P}(\tau_{j-1} < y_i^* \leq \tau_j \mid x_i) \\ &= \mathrm{P}(\tau_{j-1} < x_i'\beta + \varepsilon_i \leq \tau_j \mid x_i) \\ &= \mathrm{F}(\tau_j - x_i'\beta) - \mathrm{F}(\tau_{j-1} - x_i'\beta), \text{ for } j = 1,\ldots, J \end{aligned} \quad (4)$$

Where *F* is the logistic cumulative density function (Long, 2015). In addition, a fixed-effects ordered logit model is employed to account for unobserved heterogeneity across donor countries and over time. While the core structure of the previously described models remain unchanged, subscript *t* is incorporated to denote year *t* (Baetschmann et al., 2020; Brüderl, & Ludwig, 2015):

$$y_{it}^* = x_{it}'\beta + \alpha_i + \varepsilon_{it}, \text{ for } i = 1,\ldots, N \quad t = 1,\ldots, T \quad (5)$$

Here, the subscript *i* signifies donor country *i* and the subscript *t* indicates year *t*. The term α_i represents unobserved effects capturing time-invariant country-specific heterogeneity (Brüderl, & Ludwig, 2015). Conditional on the covariates x_{it} and the unobserved heterogeneity α_i, the probability of observing outcome *j* for country *i* at time *t* is (Baetschmann et al., 2020; Muris, 2017):

$$\begin{aligned} \mathrm{P}(y_{it} = j \mid x_{it}, \alpha_i) &= \mathrm{P}(\tau_{j-1} < y_{it}^* \leq \tau_j \mid x_{it}, \alpha_i) \\ &= \mathrm{P}(\tau_{j-1} < x_i'\beta + \alpha_i + \varepsilon_i \leq \tau_j \mid x_{it}, \alpha_i) \\ &= \mathrm{F}(\tau_j - x_i'\beta - \alpha_i) - \mathrm{F}(\tau_{j-1} - x_i'\beta - \alpha_i) \end{aligned} \quad (6)$$

3.5 Validity, reliability and ethical concerns

This section discusses the potential limitations of the study in terms of validity, reliability, and ethical concerns.

The study has a high level of reliability, primarily due to its consistent and repeatable statistical analysis (Cooper, & Schindler, 2014; Field, 2013). All data used in the study is sourced from publicly available databases, and the process of operationalisation, data collection, and analysis is carefully reported, enabling replication. In addition, the dataset and syntax used for the analysis are preserved and made available by the researcher upon request. This transparency allows for easy replication of each individual step within the analysis process (Cooper, & Schindler, 2014).

However, limitations arise concerning the quality of the data for the dependent variable. Although climate finance data is collected from reputable sources, including the OECD DAC and UNFCCC databases, the accounting methodology employed in these databases is contentious as it relies on donor countries' self-assessments of their aid and finance as climate-related (Weikmans, & Roberts, 2019). This self-reporting system raises concerns about reliability due to potential measurement and reporting errors (Richardson, 2016). Given donors' tendency to over-code and relabel funds, this subjective classification is prone to overestimations and inaccuracies (Michaelowa, & Michaelowa, 2011; Noel et al., 2023; Weikmans, & Roberts, 2019). Despite these concerns, the datasets provided by the OECD and UNFCCC are considered as the "most comprehensive and comparable data source[s] for [tracking] public climate-related aid flows" (Klöck et al., 2018, p. 900; Qian et al., 2023, p. 47; Weikmans, & Roberts, 2019). Since this issue cannot be entirely eliminated, it is crucial to keep this in mind when interpreting the results.

In terms of validity, this study aimed to achieve a high degree of validity across several dimensions. First, construct validity is strengthened by using established operationalisations from previous research, thereby ensuring that the variables measure the intended concepts (Creswell, & Creswell, 2023). Moreover, the analysis enhances internal validity by including control variables that account for extraneous influences and by using fixed-effects to control for unobserved heterogeneity. While omitted variable bias remains a possibility, the careful selection of control variables, informed by existing research, and the inclusion of year and country fixed-effects help to mitigate this concern (Brüderl, & Ludwig, 2015). Additionally, the use of multiple variables to test the same hypothesis increased the robustness of the findings (Fuchs et al., 2014). However, the external validity of this study is limited due to its exclusive focus on Annex-II Parties and its short timeframe (Creswell, & Creswell, 2023).

In the current study, ethical concerns are minimal, primarily due to the nature of the data used. By exclusively employing publicly available databases, potential ethical or privacy concerns do not present themselves. The absence of personally identifiable information further reduces these concerns, as only country-level data is utilised. However, despite the accessibility of the data, ethical responsibilities cannot be disregarded (Gliniecka, 2023). Therefore, this study remains committed to upholding ethical research principles, including transparency, verifiability, impartiality, independence, and responsible and ethical data re-use, in accordance with the Erasmus University Code of Integrity (Erasmus University Rotterdam, n.d.).

4. Empirical findings

In the following sections, the main results of the empirical analyses are presented and discussed. First, descriptive statistics are presented in Subsection 4.1 to provide a preliminary presentation of the data. Subsequently, the statistical assumptions for running an ordered logit model are reviewed in Subsection 4.2. Subsection 4.3 outlines the data analysis process. Following this, the aggregated results of the analysis are interpreted in Subsection 4.4, leading to the acceptance and/or rejection of the hypotheses.

4.1 Descriptive results

Table 1 summarises the descriptive statistics for the dependent and independent variables. The dataset consists out of 230 observations between 2011 and 2020, with each observation corresponding to a particular year within a certain donor country.

Table 1

Descriptive statistics of all variables

Variable		Percentage	N
New and additional climate finance			
	Zero	32.17%	74
	Weak	15.65%	36
	Moderate	12.17%	28
	Strong	40.00%	92
Cabinet composition			
	Hegemony of right-wing and centre parties	44.78%	103
	Dominance of right-wing and centre parties	16.09%	37
	Balance of power between left and right	21.30%	49
	Dominance of social-democratic and other left parties	10.43%	24
	Hegemony of social-democratic and other left parties	7.39%	17

Variable	Mean	SD	Min	Max	N
GDP per capita	48,212.69	19,812.14	17,283.25	10,8351.5	230
GDP growth (%)	1.195	3.273	-11.167	24.475	230
Government debt (% of GDP)	.858	.503	.185	2.583	230
Unemployment (% of civilian labour force)	.079	.050	.024	.278	230
Share of green votes	5.694	5.453	0	21.7	230
GHG evolution (% to 1990)	.958	.193	.507	1.323	230
IEAs in force	387.304	130.607	203	737	230
GHG per capita (in metric tons)	8.236	3.912	3.243	21.042	230
ODA (in USD millions)	6,456.461	8,850.476	33	38703	230
WGIs	1.377	.406	.130	1.867	230
Vulnerability	.307	.028	.244	.382	230

4.2 Statistical assumptions

The present section provides an overview of the statistical assumptions required for performing an ordered logistic regression, including multicollinearity and proportional odds (Long, 2015). Additionally, since the second model incorporates fixed-effects, the assumptions of serial correlation and homoscedasticity are tested (Brüderl, & Ludwig, 2015; De Vocht, 2019). Failure to adhere to these assumptions can result in faulty statistical inferences (Ernst, & Albers, 2017; Meuleman et al., 2015).

4.2.1 Multicollinearity

Multicollinearity occurs when one or more independent variables in the multiple regression model are highly correlated (Daoud, 2017; Meuleman et al., 2015). In cases of perfect multicollinearity, at least one independent variable can be perfectly predicted by the other independent variables (Field, 2013; Meuleman et al., 2015). This poses a problem, because strong multicollinearity can increase the standard errors of regression coefficients and make it more difficult to disentangle the net effects of each individual variable (Field, 2013; Meuleman et al., 2015). To detect the presence of multicollinearity, both a correlation matrix and a collinearity diagnostic are employed. The correlation matrix showed that the predictor variables do not have high correlations (above .80 or .90; Field, 2013; see Appendix E, Table 8). In addition, the collinearity diagnostic revealed that not all independent variables have a variance inflation factor (VIF) lower than 10, indicating some level of dependency among certain variables (Field, 2013; Meuleman et al., 2015; see Appendix E, Table 9). Consequently, the variable 'GHG emissions' with a VIF of 24.3 was excluded from the analysis, as the variable 'GHG emissions per capita' already takes into account donor's emission levels. This adjustment brought the VIFs of all variables below the threshold of 10. Since all variables meet this criterion, the assumption of absence of multicollinearity is upheld (Field, 2013; see Appendix E, Table 10).

4.2.2 Proportional odds

The proportional odds assumption implies that each explanatory variable has "the same effect on the odds, regardless of the different consecutive splits of the data" (O'Connell, 2006, p. 29). This means that the impact of each explanatory variable on the odds is assumed to be invariant across the corresponding splits of the ordinal dependent variable (O'Connell, 2006). When this assumption is violated, it indicates that the effects of one or more independent variables differ significantly across the model's cut point equations (Fullerton, & Xu, 2012). The assumption of proportional odds is examined using the Brant test, wherein a non-significant omnibus implies that the assumption is not violated (Liu, 2009). However, in the analysis, the test yielded a significant result for the "All" statistic (see Appendix E, Table 11), indicating a violation of the proportional odds assumption. To address this issue, several remedies were explored, including combining the categories of the dependent variable and excluding certain variables from the model (Long, 2015). Despite these attempts, no significant improvements were observed. Furthermore, conducting a multinomial logit model was deemed inappropriate, as it neglects the ordinal nature of the outcome variable (Harrell, 2015; Long, 2015; O'Connell, 2006), which is crucial for this study. Additionally, O'Connell (2006), Harrell (2015), and Long (2015) note that the proportional odds assumption is frequently violated. Notably, rejection of this assumption often arises with a large number of explanatory variables (Brant, 1990), a large sample size, or the inclusion of continuous explanatory variables (Allison 1999, as cited in O'Connell, 2006 and Long, 2015). While acknowledging this limitation, the violation of the proportional odds assumption typically does not significantly undermine the model's ability to provide fairly accurate predictions (Harrell, 2015).

4.2.3 Autocorrelation

Autocorrelation, also known as serial correlation, occurs when residuals are correlated with each other. The residuals should be independent, meaning that the residual of one observation should not depend on the residuals of other observations (Meuleman et al., 2015). However, non-independence is commonly observed in time series data, as "the observation at time point t will probably depend to some extent on how the situation was at time point $t-1$" (Meuleman et al., 2015, p. 95). Violating the autocorrelation assumption affects the standard errors of the regression parameters, while leaving the parameter estimates intact, thereby preserving the validity of the regression analysis (Field, 2013; Meuleman et al., 2015). To test for autocorrelation, the Breusch-Pagan Lagrange Multiplier test was performed (Le Gallo et al., 2020). The test results indicated a violation of the autocorrelation assumption, as the test statistic was significant (see Appendix E, Figure 4). To account for serial correlation, standard errors were clustered at the group/country level (Hoechle, 2007; Meuleman et al., 2015).

4.2.4 Homoscedasticity

The assumption of homoscedasticity holds when the variance of the residuals is constant across all observations, indicating equal variances of the residuals at each level of the predictors. Violation of this assumption results in heteroscedasticity, where the variance of the residuals varies systematically (Field, 2013; Meuleman et al., 2015). Such non-constant error variance will result in biased confidence intervals and significance tests for the parameter estimates (Field, 2013; Meuleman et al., 2015). To check for homoscedasticity, the Modified Wald test for groupwise heteroscedasticity was conducted (Baum, 2001). The significant test statistic indicated heteroscedasticity (see Appendix E, Figure 5), thus violating the homoscedasticity assumption. However, standard errors were clustered at the group/country level to obtain heteroscedasticity-consistent standard errors (Hoechle, 2007).

4.3 Analysis

The collected data was analysed using STATA 18. Prior to the main data analysis, several preparatory steps were taken. First, the continuous dependent variable was divided into four ordered categories: ‘zero’, ‘weak’, ‘moderate’, and ‘strong’. Quantiles were used instead of quartiles to ensure that all zero values were grouped together (Field, 2013). Second, variables with highly skewed distributions, including GDP per capita, IEAs, GHG emissions, and ODA, were log-transformed to normalise the data and reduce data variability (Feng et al., 2014). Third, due to the strong correlations between the six WGIs (see Appendix C, Table 5), an average score was calculated to avoid multicollinearity issues (Halimanjaya, & Papyrakis, 2015; Noel et al., 2023). Following data preparation and the generation of descriptive statistics, the assumptions required for running an ordered logit model and a fixed-effects ordered logit model were checked. Subsequently, an ordered logit model with and without fixed-effects was performed. To address potential omitted variable bias and to identify robust determinants of new and additional climate finance provision (Fuchs et al., 2014), year and country fixed-effects were included in the second model of the ordered logistic regression. The control variables were included in both models as the focus was not on their mediating or moderating effects.

4.4 Disaggregated results

Table 2 presents the results of the ordered logit model, analysing the influence of country characteristics on the provision of new and additional climate finance. Model I displays the effects of the independent variables related to economic capability and political commitment, along with the control variables. Model II further incorporates year and country fixed-effects to account for unobserved time-invariant and country-specific factors, thereby enhancing the robustness of the analysis.

Table 2 shows that both models are statistically significant, as indicated by their p-value (i.e. $p <.01$), implying an improved model fit (Wald Chi^2 Model I = 125.57; Wald Chi^2 Model II = 3342.68). Model I explains approximately 22.86% of the variance in the dependent variable (adjusted $R^2 =.2286$), while Model II accounts for 59.83% of the variance (adjusted $R^2 =.5983$). This indicates that the explanatory power of the regression model is significantly improved by the inclusion of unobserved year-invariant and country-specific factors.

4.4.1 Economic capability

Economic capacity

The regression analysis reveals contrasting findings regarding countries' economic capacity. Contrary to the expectations, GDP per capita is negatively associated with new and additional climate finance provision. However, this correlation is only observed after controlling for year-invariant and country-specific factors ($\beta = -49.4918$, $p < .01$). This suggests that unobserved heterogeneity significantly influences and strengthens the magnitude of this relationship, indicating that countries with higher GDP per capita are more likely to fall into the lower categories of new and additional climate finance provision. Conversely, the relationship between GDP growth and new and additional climate finance provision is found to be insignificant in both models. This implies that GDP growth does not affect the probability of a country falling into higher or lower categories of new and additional climate finance provision, even when accounting for year and country fixed-effects.

Collectively, these findings provide evidence against the first hypothesis, which posits that donor countries with more economic capacity are more likely to provide new and additional climate finance. Hence, the 'Respective Capabilities' aspect of the CBDR&RC principle seems to carry more symbolic than literal weight, especially for Annex-II Parties with higher income levels. Consequently, H_1 is not supported by the results of the analysis and must therefore be rejected.

Fiscal constraints

From donor countries' fiscal constraints perspective, the analysis yields the anticipated results. Consistent with expectations, countries with higher levels of government debt have an increased probability to be in the lower categories of new and additional climate finance provision. Specifically, as government debt increases, the likelihood of a country falling into a higher category of new and additional climate finance provision decreases. This correlation persists and increases in magnitude when accounting for unobserved country-invariant and year-specific factors ($\beta_1 = -1.6527$, $p < .01$; $\beta_2 = -4.9690$, $p < .1$). Similarly, the negative and significant coefficient of unemployment rate in both models indicates that countries with higher unemployment rates are more likely to fall into the lower categories of new and additional climate finance provision, with this correlation being substantially stronger in Model II ($\beta_1 = -21.8956$, $p < .01$; $\beta_2 = -50.8190$, $p < .05$).

These results strongly support the second hypothesis, which states that donor countries with tighter fiscal constraints are less likely to provide new and additional climate finance, thereby confirming H_2. This underscores the critical influence of donor countries' fiscal health on their ability to honour their climate finance commitments, particularly in terms of providing new and additional climate finance.

4.4.2 Political commitment

Environmentally-concerned population

The presence of an environmentally-concerned population does not seem to influence countries' provision levels of new and additional climate finance, as indicated by the insignificant relationship between the share of green party votes in parliamentary elections and new and additional climate finance provision across both models. This suggests that variations in green party electoral support do not correlate with a country's likelihood to provide either higher or lower levels of new and additional climate finance. Since no significant relationship is found, the third hypothesis, which proposes that donor governments with a larger environmentally-concerned population are more likely to provide new and additional climate finance, is rejected.

Government environmental preferences

The analysis of government environmental preferences shows mixed results. Contrary to expectations, this study finds that the correlation between cabinet composition and new and additional climate finance provision is statistically insignificant in both models. This outcome suggests that the makeup of a cabinet does not significantly influence a country's likelihood to fall into higher or lower categories of new and additional climate finance provision. In contrast, the analysis reveals a positive correlation between GHG emissions evolution levels and new and additional climate finance provision, with a substantial increase in this relationship's magnitude in the second model ($\beta_1 = 2.1003$, $p < .05$; $\beta_2 = 32.7990$, $p < .01$). Specifically, nations with higher GHG emissions relative to their 1990 baseline are more likely to be in the higher categories of new and additional climate finance provision, which contradicts initial expectations. Furthermore, the impact of participation in IEAs on new and additional climate finance provision varies across the models. In the first model, the negative and significant coefficient of IEAs suggests that countries participating in more IEAs are more likely to fall into the lower categories of new and additional climate finance provision ($\beta_1 = -4.8908$, $p < .01$). However, when controlling for unobserved time-invariant and country-specific factors, increased IEAs participation correlates with a higher likelihood of being in the higher categories of new and additional climate finance provision ($\beta_2 = 40.9790$, $p < .1$). This inversion of the relationship between Model I and Model II is accompanied by a significant increase in its magnitude.

Only IEAs participation supports the fourth hypothesis, which posits that donor governments with stronger environmental preferences are more likely to provide new and additional climate finance. Although the influence of cabinet composition is not confirmed, and there is an unexpected positive impact of GHG emissions evolution levels, the positive influence of participation in IEAs is evident. This underscores that GHG performance and international environmental cooperation are crucial factors in determining countries' provision levels of new and additional climate finance.

Donor responsibility

The regression analysis finds a negative correlation between per capita GHG emissions and new and additional climate finance provision ($\beta_2 = -1.8989$, $p < .01$), but only when controlling for year and country fixed-effects. This suggests that larger per capita emitters are more likely to fall into lower categories of new and additional climate finance provision, when accounting for unobserved heterogeneity. Specifically, as a country's per capita GHG emissions increase, the likelihood of it falling into a higher category of new and additional climate finance provision decreases. Consequently, these results corroborate the last hypothesis, indicating that donor countries that bear greater responsibility for climate change are less likely to provide new and additional climate finance. Similar to the 'Respective Capabilities' aspect of the CBDR&RC principle, the 'Common But Differentiated Responsibilities' part does not seem to hold significant sway on more responsible Annex-II Parties. These findings confirm the fifth hypothesis.

4.4.3 Control variables

Among the control variables, only ODA has a statistically significant effect on new and additional climate finance provision in both models. Higher ODA allocations are associated with a greater likelihood of a country falling into higher categories of new and additional climate finance provision ($\beta_1 = 1.3336$, $p < .01$; $\beta_2 = 10.4482$, $p < .01$). Conversely, countries with stronger institutional capacity are more likely to fall into lower categories of new and additional climate finance provision ($\beta_1 = -1.7994$, $p < .05$). However, this correlation disappears when fixed-effects are included. Similarly, countries that are more vulnerable to climate change impacts tend to fall into lower categories of new and additional climate finance provision (β_1 = -37.4978, p <.01). Yet, this significant relationship also vanishes when unobserved year-invariant and country-specific factors are taken into account.

Table 2

Ordered logit model

	Dependent variable: NACF	
	(I)	(II)
Log (GDP per capita)	-1.1409	-49.4918***
	(0.7388)	(17.2136)
GDP growth (%)	-0.0951	0.0558
	(0.0593)	(0.2024)
Government debt (% of GDP)	-1.6527***	-4.9690*
	(0.4497)	(2.8959)
Unemployment (% of civilian labour force)	-21.8956***	-50.8190**
	(5.6438)	(23.0242)
Share of green votes	0.0530	-0.0178
	(0.0420)	(0.0806)
Cabinet composition	0.0711	-0.2778
	(0.1169)	(0.2440)
GHG evolution (% to 1990)	2.1003**	32.7990***
	(1.0140)	(8.5936)
Log (IEAs)	-4.8908***	40.9790*
	(0.9627)	(21.4900)
GHG per capita	0.0452	-1.8989***
	(0.0497)	(0.4834)
Log (Total ODA)	1.3336***	10.4482***
	(0.2213)	(2.4533)
Average WGI	-1.7994**	-5.4050
	(0.8401)	(4.1586)
Vulnerability	-37.4978***	30.1851
	(7.6310)	(85.3976)
Tau 1	-46.1886***	-221.6422
	(11.1787)	(153.4619)
Tau 2	-45.0772***	-218.6519
	(11.1495)	(153.4244)
Tau 3	-44.2545***	-216.7023
	(11.1251)	(153.4107)
Year fixed-effects	NO	YES
Country fixed-effects	NO	YES
Observations	230	230
Number of countries	23	23
Psuedo R-squared	0.2286	0.5983
Wald Chi^2	125.57***	3342.68***

Note. Robust standard errors are in parentheses below the coefficients.
*** p<0.01, ** p<0.05, * p<0.1.

5. Conclusion and discussion

The commitment of developed countries to collectively mobilise and provide new and additional climate finance to developing nations has been largely unmet. While some countries have honoured this promise, many have fallen short, raising concerns about the increased risk of failing to meet climate finance targets. As we approach the setting of a NCQG on climate finance at the upcoming COP29, it is of great importance to study the factors contributing to these disparities in fulfilling this pledge. This paper employs an ordered logit model, both with and without fixed-effects, to examine the influence of country characteristics on nations' provision levels of new and additional - exceeding their 2009 development finance levels - climate finance. The study focuses on economic capability and political commitment determinants among 23 Annex-II Parties over the period from 2011 to 2020.

The empirical findings show that donor countries' provision levels of new and additional climate finance is influenced by both their economic capability and political commitment. Economic capacity and fiscal constraints both emerged as limiting factors, with wealthier countries and those with high government debt and unemployment levels being less likely to provide the highest levels of new and additional climate finance. However, GDP growth did not significantly impact countries' provision levels. From a political perspective, while the presence of an environmentally-concerned population did not significantly affect countries' financial contributions, governments with environmental preferences did wield limited influence, as confirmed by one – IEAs participation – out of the three variables analysed. Although cabinet composition was not a decisive factor, higher contributors of new and additional climate finance were more likely to participate in a greater number of IEAs and experience higher GHG emissions evolution levels. Additionally, the largest current polluters, bearing significant responsibility for climate change, tend to shoulder the smallest share of the financial burden.

The study's most intriguing finding is the negative association between GDP per capita and new and additional climate finance provision. This contradicts previous research, which suggests that greater economic capacity is correlated with higher climate finance contributions (Klöck et al., 2018; Li, & Reuveny, 2006). The marginal effects, outlined in Table 3, reveal a change in sign when reaching the highest new and additional climate finance category, indicating a non-linear relationship. This suggests that beyond a certain threshold, higher GDP per capita correlates with decreased new and additional climate finance contributions. While richer countries generally contribute more, there seems to be a point where further increases in GDP per capita are associated with decreased contributions. This counterintuitive finding requires further research, as the reasons behind this negative finding can only be speculated upon. Initially, skewed data categories were considered as a potential explanation. However, the negative association is also observed in the fixed-effects model (see Appendix D, Table 6), suggesting a more complex underlying cause. Moreover, the insignificant correlation between GDP growth and new and additional climate finance can be explained by Qian et al.'s (2023) findings, indicating that changes in GDP growth rates exert a long-term rather than short-term influence on donors' climate finance provision.

Table 3

Marginal effects of GDP per capita

	1	2	3	4
Log (GDP capita)	2.529847***	.6175174*	.2253061	-3.372671**

*** p<0.01, ** p<0.05, * p<0.1.

Similar to Klöck et al. (2018) and Halimanjaya and Papyrakis (2015), the analysis finds no significant correlations between the size of an environmentally-concerned population, cabinet composition, and new and additional climate finance provision. Future research should explore the reasons behind these insignificant relationships. One possible explanation for the lack of impact of public environmental concern could be the limited political power of green parties. Green parties, often found in opposition or as junior partners in coalition governments, may lack sufficient political power or influence to effect changes in national climate finance policies (Klöck et al., 2018; Qian et al., 2023). Consequently, their limited power might hinder their ability to secure higher levels of new and additional climate finance. Furthermore, a left-leaning cabinet composition does not necessarily equate to (external) environmental commitments (Halimanjaya, & Papyrakis, 2015). Left-wing governments may prioritise domestic environmental issues (Hicks et al., 2008) and/or employment (Milner, & Judkins, 2004) over environmental action abroad. This might explain why cabinet composition alone does not predict the level of new and additional climate finance provided by countries.

The unexpected finding that countries with higher GHG emissions evolution levels tend to be larger contributors of new and additional climate finance raises questions about whether GHG evolution is an accurate measure of government environmental preferences, despite its use by Noel et al. (2023). A possible reason for this paradoxical finding is the time lag between climate finance contributions and their impact on emissions reductions. Investments in clean technologies and sustainable practices often take time to translate into tangible emissions reductions (Raghutla, & Chittedi, 2023; Zhang et al., 2023). Studies by Shao et al. (2021) and Zhang et al. (2023) support this notion, indicating that green technological innovation has a significant negative impact on CO_2 emissions in the long run rather than in the short-term. However, this seemingly contradictory relationship requires further investigation to fully understand the underlying dynamics.

This analysis highlights the importance of considering country-level unobserved factors and time-specific influences when examining determinants of new and additional climate finance provision, as illustrated by the differences between Model I, which excludes fixed-effects, and Model II, which includes year and country fixed-effects. The substantial changes in coefficient magnitudes and statistical significance when fixed-effects are introduced show the limitations of models that do not account for such heterogeneity. While Model I's results provide preliminary insights, they are potentially susceptible to omitted variable bias (Brüderl, & Ludwig, 2015; Wolf, & Best, 2015). These results may reflect the influence of omitted variables related to specific donors or years, thereby possibly masking the "true" effects of the explanatory variables (Fuchs et al., 2014). This is evidenced by the alterations in both the direction and significance of relationships when fixed-effects are included. For instance, significant relationships observed in Model I became insignificant in Model II (i.e. WGI and vulnerability), suggesting that these initial associations were driven by unobserved factors which are controlled for with fixed-effects. Conversely, relationships shifting from non-significance in Model I to significance in Model II (i.e. GDP per capita), indicate that Model I omits important unobserved factors that are affecting these relationships. In addition, the significant improvement in model fit with fixed-effects, demonstrated by the 36.97% increase in pseudo R-squared, further underscores the importance of accounting for unobserved heterogeneity.

While incorporating year and country fixed-effects improves the robustness of the model, this approach also has its limitations. It focuses on within-country changes over time (Fuchs et al., 2014), which could lead to isolating the effects of variables that exhibit consistent cross-country and cross-temporal influences (Fortin-Rittberger, 2015). For instance, global trends, such as economic crises, or international climate conferences might similarly affect climate finance provisions across all countries in a specific year, potentially obscuring their actual relationship with new and additional climate finance provision (Fuchs et al., 2014). Consequently, variables that are significant in Model I but insignificant in Model II may still be relevant, as their influence on new and additional climate finance provision could be consistent across countries and over time. This study design limitation may have led to underestimating the impact of variables that became insignificant in the second model, but could have had consistent cross-country and temporal effects on new and additional climate finance provision.

A second limitation of this study lies in the categorisation of the continuous dependent variable. The distribution of observations across the four categories is uneven, with two of the categories being significantly larger than the other two. While the rationale for this approach is outlined in Section 3.1.1, it presents a potential limitation, specifically for the third category which contains only 28 observations. This is evident in the marginal effects table (see Appendix F, Table 12), where the effects for this category may not be significant due to the reduced ability to detect true differences with a smaller sample size (Long, 2015). To address this limitation, future research could explore alternative models better suited for continuous dependent variables with skewed distributions, such as the Tobit model (Boulton, & Williford, 2018).

Thirdly, this study finds a negative correlation between GHG emissions per capita and new and additional climate finance provision, consistent with previous research by Klöck et al. (2018). However, using per capita GHG emissions as a sole indicator of donor responsibility presents limitations, as it focuses only on country's current emissions, neglecting historical contributions (Tan, 2023). Certain Annex-II Parties may have historically emitted more GHGs than they do presently, which is not accounted for. Future research should therefore consider incorporating historical GHG emissions data for a fairer assessment.

A last shortcoming of this study, which is previously outlined, relates to the data quality of the dependent variable. The reliance on donor-reported data from the OECD and UNFCCC databases potentially affects the accuracy of the findings. Donors' subjective classification of their aid and finance as climate-related can lead to overestimations and reporting errors (Michaelowa & Michaelowa, 2011; Noel et al., 2023; Weikmans, & Roberts, 2019).

6. Recommendations

Based on the findings of this study, two key policy recommendations are formulated. First, the negative impact of fiscal constraints on countries' new and additional climate finance provision highlights the dependency of climate finance on the fiscal health of donor countries. To ensure continuous support for climate action, implementing resilient economic policies and exploring innovative financing mechanisms are crucial. One promising strategy involves issuing green bonds dedicated to climate finance. These bonds, which function as fixed-income securities, provide a stable and reliable source of funding (Banga, 2019). Additionally, alternative financing methods that do not solely rely on government budgets should be explored. Given the prevalence of European Union (EU) members among donor countries, establishing an EU Climate Finance Stability Fund could serve as a financial buffer during economic downturns. To generate income for this fund, two revenue streams are proposed. The first is a Climate Damages Tax, a levy on fossil fuel extraction based on the amount of carbon dioxide equivalent embedded within the fossil fuel (Sharma, & Hillman, 2024). This "polluter pays" approach aims to hold the fossil fuel industry accountable, while generating significant new and additional resources for climate action, with estimates reaching 720 billion dollars by 2023 (Sharma, & Hilman, 2024). Another promising approach involves redirecting revenues from existing carbon pricing mechanisms towards this climate finance fund. For instance, the EU's Carbon Border Adjustment Mechanism (CBAM) is designed to generate funds for the EU budget and reduce dependency on Member States' contributions (Pleeck, & Mitchell, 2023). Currently, CBAM revenues are intended to finance the repayment of borrowing under NextGenerationEU, the EU's COVID-19 recovery package, rather than to financially support developing countries in their climate change adaptation and mitigation efforts (McLoughlin, 2024; Pleeck, & Mitchell, 2023). Reallocation of this revenue could significantly increase climate finance contributions.

Second, the positive correlation between participation in IEAs and higher levels of new and additional climate finance provision underscores the importance of strengthening global partnerships and commitments through these agreements. Collaboration through participation in IEAs is crucial to collectively address global climate change and achieve climate finance targets.

Bibliography

Achampong, L. (2023). In Focus: Reforming Climate Finance. In OECD (Eds.), *Development Co-operation Report 2023. Debating the Aid System* (pp. 71-81). OECD Publishing. https://read.oecd-ilibrary.org/development/development-co-operation-report-202398de3607-en#page2.

Alayza, N., Larsen, G., & Waskow, D. (2024, May 29). What Could the New Climate Finance Goal Look Like? 7 Elements Under Negotiation. *World Resources Institute*. https://www.wri.org/insights/ncqg-key-elements.

Allison, P.D. (1999). *Logistic Regression Using the SAS System: Theory and Application*. SAS Institute. https://www.wiley.com/en-ae/Logistic+Regression+Using+the+SAS+System%3A+Theory+and+Application-p-9780471221753.

Armingeon, K., Engler, S., Leemann, L., & Weisstanner, D. (2023). *Comparative Political Data Set 1960-2021*. University of Zurich, Leuphana University Lueneburg, and University of Lucerne. https://cpds-data.org/data/.

Baetschmann, G., Ballantyne, A., Staub, K.E., & Winkelmann, R. (2020). Feologit: A New Command for Fitting Fixed-Effects Ordered Logit Models. *The Stata Journal, 20*(2), 253-275.

Banga, J. (2019). The Green Bond Market: A Potential Source of Climate Finance for Developing Countries. *Journal of Sustainable Finance & Investment, 9*(1), 17-32.

Baum, C.F. (2001). Residual Diagnostics for Cross-Section Time Series Regression Models. *The Stata Journal, 1*(1), 101-104.

Best, H., & Wolf, C. (2015). Logistic Regression. In H. Best & C. Wolf (Eds.), *The Sage Handbook of Regression Analysis and Causal Inference* (pp. 153-171). Sage Publications. http://ndl.ethernet.edu.et/bitstream/123456789/26799/1/122.Henning%20Best%2C%20Christof%20Wolf-.pdf#page=338.

Bodenstein, T., & Kemmerling, A. (2015). A Paradox of Redistribution in International Aid? The Determinants of Poverty-Oriented Development Assistance. *World Development, 76*, 359-369.

Boulton, A.J., & Williford, A. (2018). Analyzing Skewed Continuous Outcomes With Many Zeros: A Tutorial for Social Work and Youth Prevention Science Researchers. *Journal of the Society for Social Work and Research, 9*(4), 721-740.

Brant, R. (1990). Assessing Proportionality in the Proportional Odds Model for Ordinal Logistic Regression. *Biometrics, 46*(4), 1171-1178.

Brown, J., Cantore, N., & Te Velde, D.W. (2010). *Climate Financing and Development: Friends or Foes?* Overseas Development Institute. http://environmentportal.in/files/Climate%20financing%20and%20development.pdf.

Brüderl, J., & Ludwig, V. (2015). Fixed-Effects Panel Regression. In H. Best & C. Wolf (Eds.), *The Sage Handbook of Regression Analysis and Causal Inference* (pp. 327-357). Sage Publications. http://ndl.ethernet.edu.et/bitstream/123456789/26799/1/122.Henning%20Best%2C%20Christof%20Wolf-.pdf#page=338.

Buchner, B., Naran, B., Padmanabhi, R., Stout, S., Strinati, C., Wignarajah, D., Miao, G., Connolly, J., & Marini, N. (2023). *Global Landscape of Climate Finance 2023*. Climate Policy Initiative. https://www.climatepolicyinitiative.org/wp-content/uploads/2023/11/Global-Landscape-of-Climate-Finance-2023.pdf.

Carter, N. (2013). Greening the Mainstream: Party Politics and the Environment. *Environmental Politics, 22*(1), 73-94.

Ciplet, D., Adams, K.M., Weikmans, R., & Roberts, J.T. (2018). The Transformative Capability of Transparency in Global Environmental Governance. *Global Environmental Politics, 18*(3), 130-150.

Cooper, D.R., & Schindler, P.S. (2014). *Business Research Methods*. McGraw-Hill/Irwin. https://contents.lspr.ac.id/2022/05/Donald-R-Cooper-Pamela-S-Schindler-Business-Research-Methods.pdf.

Corvino, F. (2023). The Forward-Looking Polluter Pays Principle for a Just Climate Transition. *Critical Review of International Social and Political Philosophy,* 1-28.

Creswell, J.W., & Creswell, J.D. (2023). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*. SAGE Publications. file:///C:/Users/Gwenyth/Downloads/John%20W.%20Creswell,%20J.%20David%20Creswell%20-%20Research%20Desig n%20Qualitative,%20Quantitative,%20and%20Mixed%20Methods%20Approaches%20(2022,%20SAGE%20Publications)%20-%20libgen.li-8.pdf.

Daoud, J.I. (2017). Multicollinearity and Regression Analysis. *Journal of Physics: Conference Series, 949*(1), 1-6.

De Vocht, A. (2019). *Basishandboek SPSS 25: Voor SPSS 25 & SPSS Subscription*. Bijleveld Press.

Eklöf, G. (2022). *Swedish and International Climate Finance. Key Facts, Figures and Concerns*. Concord Sweden. https://concord.se/wp-content/uploads/2022/09/swedish-and-international-climate-finance-2022.pdf.

Erasmus University Rotterdam. (n.d.). *Our Code of Integrity*. https://www.eur.nl/en/media/2021-12-code-integrity-eur.

Ernst, A.F., & Albers, C.J. (2017). Regression Assumptions in Clinical Psychology Research Practice – A Systematic Review of Common Misconceptions. *PeerJ, 5,* 1-16.

Eyckmans, J., Fankhauser, S., & Kverndokk, S. (2016). Development Aid and Climate Finance. *Environmental and Resource Economics*, *63*, 429-450.

Feng, C., Wang, H., Lu, N., Chen, T., He, H., Lu, Y., & Tu, X.M. (2014). Log-Transformation and its Implications for Data Analysis. *Shanghai Archives of Psychiatry, 26*(2), 105-109.

Field, A. (2013). *Discovering Statistics Using IBM SPSS Statistics*. SAGE. https://rauterberg.employee.id.tue.nl/lecturenotes/DBB150/references/Field-2013%20Discovering%20Statistics%20Using%20IBM%20SPSS-ed4.pdf.

Fortin-Rittberger, J. (2015). Time-Series Cross-Section. In H. Best & C. Wolf (Eds.), *The Sage Handbook of Regression Analysis and Causal Inference* (pp. 387-408). Sage Publications. http://ndl.ethernet.edu.et/bitstream/123456789/26799/1/122.Henning%20Best%2C%20Christof%20Wolf-.pdf#page=338.

Fuchs, A., Dreher, A., & Nunnenkamp, P. (2014). Determinants of Donor Generosity: A Survey of the Aid Budget Literature. *World Development, 56*, 172–199.

Fullerton, A.S., & Xu, J. (2012). The Proportional Odds with Partial Proportionality Constraints Model for Ordinal Response Variables. *Social Science Research, 41*(1), 182-198.

Gilder, A., & Rumble, O. (2020). *Improving Sub-Saharan African Access to Climate Change Finance: An Alternative View. Policy Briefing 194.* SAIIA. https://saiia.org.za/wp-content/uploads/2020/04/Policy-Briefing-194-gilder-rumble.pdf.

Gliniecka, M. (2023). The Ethics of Publicly Available Data Research: A Situated Ethics Framework for Reddit. *Social Media + Society, 9*(3), 1-11.

Green, J.A. (2021). Too Many Zeros and/or Highly Skewed? A Tutorial on Modelling Health Behaviour as Count Data With Poisson and Negative Binomial Regression. *Health Psychology and Behavioral Medicine, 9*(1), 436-455.

Greene, Z.D., & Licht, A.A. (2018). Domestic Politics and Changes in Foreign Aid Allocation: The Role of Party Preferences. *Political Research Quarterly, 71*(2), 284-301.

Grilli, L., & Rampichini, C. (2014). Ordered Logit Model. In A.C. Michalos (Ed.), *Encyclopedia of Quality of Life and Well-Being Research* (pp. 4510-4513). Springer. https://labdisia.disia.unifi.it/grilli/files/Papers/Ordered_Logit.pdf.

Halimanjaya, A. (2016). Allocating Climate Mitigation Finance: A Comparative Analysis of Five Major Green Donors. *Journal of Sustainable Finance & Investment, 6*(3), 161-185.

Halimanjaya, A., & Papyrakis, E. (2015). Donor Characteristics and the Allocation of Aid to Climate Mitigation Finance. *Climate Change Economics*, *6*(3), 1-25.

Harrell, F.E. (2015). *Regression Modeling Strategies: With Applications to Linear Models, Logistic and Ordinal Regression, and Survival Analysis.* Springer. https://link.springer.com/book/10.1007/978-3-319-19425-7.

Harvey, F. (2023, November 16). Rich Countries Hit $100bn Climate Finance Goal Two Years Late, Data Shows. *The Guardian.* https://www.theguardian.com/global-development/2023/nov/16/rich-countries-hit-climate-finance-goal-two-years-late-data.

Hattle, A., Nordbo, J., Myrup, A., Elming, L., Sørensen, R.B., Achton, I., Knudsen, A.B., Bentsen, E., Nygaard, L.P., Mattson, C., & Hansen, M. (2023). *Seeing Double: Decoding the 'Additionality' of Climate Finance*. CARE. https://www.care-international.org/sites/default/files/2023-09/Seeing-Double-2023_15.09.23_larger.pdf.

Hicks, R.L., Parks, B.C., Roberts, J.T., & Tierney, M.J. (2008). *Greening Aid? Understanding Environmental Assistance to Developing Countries*. Oxford University Press. https://bo oks.google.nl/books?id=yWwVDAAAQBAJ&printsec=frontcover&source=gbs_book other_versions_r&redir_esc=y#v=onepage&q&f=false.

Hoechle, D. (2007). Robust Standard Errors for Panel Regressions With Cross-Sectional Dependence. *The Stata Journal*, *7*(3), 281-312.

IMF (n.d.). *General Government Gross Debt: Percent of GDP*. https://www.imf.org/external/datamapper/GGXWDG_NGDP@WEO/OEMDC/ADVEC/WEOWORLD.

IPCC. (2023). *Climate Change 2023: Synthesis Report. Summary for Policymakers*. https://www.ipcc.ch/report/ar6/syr/downloads/report/IPCC_AR6_SYR_SPM.pdf.

Jensen, L., & Roniger, J. (2023). *International Climate Finance: Status Quo, Challenges and Policy Perspectives*. European Parliamentary Research Service. https://www.europarl.europa.eu/RegData/etudes/BRIE/2023/754616/EPRS_BRI(2023)754616_EN.pdf.

Kaufmann, D., & Kraay, A. (2023). *Worldwide Governance Indicators, 2023 Update*. World Bank Group. https://www.worldbank.org/en/publication/worldwide-governance-indicators.

Kawabata, T. (2023). Climate Finance Governance Through Transnational Networks. *Journal of Sustainable Finance & Investment, 13*(4), 1624-1643.

Kenny, C. (2020a). *Official Development Assistance, Global Public Goods, and Implications for Climate Finance*. *CGD Policy Paper 188.* Centre for Global Development. https://www.cgdev.org/sites/default/files/PP188-Kenny-ODA-GPGs-Full.pdf.

Kenny, C. (2020b, October 27). On Aid and Climate, Don't Make the Poor Pay Twice. *Center For Global Development.* https://www.cgdev.org/blog/aid-and-climate-dont-make-poor-pay-twice.

Khan, M.R., & Munira, S. (2021). Climate Change Adaptation as a Global Public Good: Implications for Financing. *Climate Change, 167*(50), 1-18.

Klöck, C., Molenaers, N., & Weiler, F. (2018). Responsibility, Capacity, Greenness or Vulnerability? What Explains the Levels of Climate Aid Provided by Bilateral Donors? *Environmental Politics, 27*(5), 892-916.

Lee, C.C., Li, X., Yu, C.H., & Zhao, J. (2022). The Contribution of Climate Finance Toward Environmental Sustainability: New Global Evidence. *Energy Economics*, 111, 1-10.

Le Gallo, J., López, F.A., & Chasco, C. (2020). Testing for Spatial Group-Wise Heteroskedasticity in Spatial Autocorrelation Regression Models: Lagrange Multiplier Scan Tests. *The Annuals of Regional Science, 64*(2), 287-312.

Li, Q., & Reuveny, R. (2006). Democracy and Environmental Degradation. *International Studies Quarterly, 50*(4), 935-956.

Liu, X. (2009). Ordinal Regression Analysis: Fitting the Proportional Odds Model Using Stata, SAS and SPSS. *Journal of Modern Applied Statistical Methods, 8*(2), 632-645.

Long, J.S. (2015). Regression Models for Nominal and Ordinal Outcomes. In H. Best & C. Wolf (Eds.), *The Sage Handbook of Regression Analysis and Causal Inference* (pp. 173-203). Sage Publications. http://ndl.ethernet.edu.et/bitstream/123456789/26799/1/122.Henning%20Best%2C%20Christof%20Wolf-.pdf#page=338.

McLoughlin, E. (2024). *Carbon Border Adjustment Mechanism*. Library & Research Service. https://data.oireachtas.ie/ie/oireachtas/libraryResearch/2024/2024-04-05_l-rs-note-carbon-border-adjustment-mechanism_en.pdf.

Meuleman, B., Loosveldt, G., & Emonds, V. (2015). Regression Analysis: Assumptions and Diagnostics. In H. Best & C. Wolf (Eds.), *The Sage Handbook of Regression Analysis and Causal Inference* (pp. 83-110). Sage Publications. http://ndl.ethernet.edu.et/bitstream/123456789/26799/1/122.Henning%20Best%2C%20Christof%20Wolf-.pdf#page=338.

Michaelowa, A., & Michaelowa, K. (2011). Coding Error or Statistical Embellishment? The Political Economy of Reporting Climate Aid. *World Development, 39*(11), 2010-2020.

Michaelowa, K., & Namhata, C. (2022). Climate Finance as Development Aid. In A. Michaelowa & A.K. Sacherer (Eds.), *Handbook of International Climate Finance* (pp. 62-80). Edward Elgar Publishing. https://books.google.nl/books?hl=nl&lr=&id= mW-VEAAAQBAJ&oi=fnd&pg=PA62&dq=climate+finance+on+ODA&ots=d1Ua7QVAzL&sig=Ay9gP-Y_3dvSWgZMHmHcLaJtCAU#v=onepage&q=climate%20finance%20on%20ODA&f=false.

Miller, M., Roger, L., Cao, Y., & Prizzon, A. (2023). *Where Has the Money Come From to Finance Rising Climate Ambition?* ODI. https://odi.cdn.ngo/media/documents/DPF_EA_Where_has_the_money_come_from_to_finance_rising_climate_ambition_UEXBuVX.pdf.

Milner, H.V., & Judkins, B. (2004). Partisanship, Trade Policy, and Globalization: Is There a Left–Right Divide on Trade Policy? *International Studies Quarterly, 48*(1), 95-119.

Mitchell, I., Ritchie, E., & Tahmasebi, A. (2021). *Is Climate Finance Towards $100 Billion "New and Additional"? CGD Policy Paper 205*. Center for Global Development. https://www.cgdev.org/sites/default/files/PP205-Mitchell-Ritchie-Tahmasebi-Climate-Finance.pdf.

Mitchell, R.B. (2022). *International Environmental Agreements Database Project*. University of Oregon. https://iea.uoregon.edu/.

Munira, S., Bashar, R., Easher, T.H., & Khan, M.R. (2021). Climate Finance in the UNFCCC Negotiations: Bridging Gaps with Lessons Learnt. Climate Change in Bangladesh: A Cross-Disciplinary Framework. In Md. Jakariya & Md. N. Islam (Eds.), *Climate Change in Bangladesh: A Cross-Disciplinary Framework* (pp. 1-24). Springer International Publishing. https://www.icccad.net/wp-content/uploads/2021/08/Munira-S-Bashar-R-Huq-TH-Khan-MR-2021-CF-at-UNFCCC.pdf.

Muris, C. (2017). Estimation in the Fixed-Effects Ordered Logit Model. *The Review of Economics and Statistics, 99*(3), 465-477.

ND-GAIN. (2023). *University of Notre Dame Global Adaptation Initiative: Country Index Technical Report*. University of Notre Dame. https://gain.nd.edu/assets/522870/nd_gain_countryindextechreport_2023_01.pdf.

Neumayer, E (2004). The Environment, Left-wing Political Orientation and Ecological Economics. *Ecological Economics, 51*(3–4), 167–175.

Noel, L.N., Bayramoglu, B., & Dequet, A. (2023). Are International Climate Transfers Really Climate-Related? Extent and Determinants of Donor Countries' Miscoding. In N.L. Noel (Ed.), *International Transfers for Climate Justice: Determinants, Objectives and Impacts of Climate Finance* [Doctoral dissertation] (pp. 109-161). Université Paris-Saclay. https://theses.hal.science/tel-04259968/file/112655_NOEL_2023_archivage.pdf.

Noel, L.N. (2023). International Climate Transfers: Have They Been Effective? In N.L. Noel (Ed.), *International Transfers for Climate Justice: Determinants, Objectives and Impacts of Climate Finance* [Doctoral dissertation] (pp. 163-245). Université Paris-

Saclay. https://theses.hal.science/tel-04259968/file/112655_NOEL_2023_archivage.pdf

O'Connell, A.A. (2006). *Logistic Regression Models for Ordinal Response Variables*. SAGE Publications. https://d1wqtxts1xzle7.cloudfront.net/63147370/Ordinal_logistic_book20200430-64277-v93bfo-libre.pdf?1588252299=&response-content-disposition=inline%3B+filename%3DOrdinal_logistic_book.pdf&Expires=1716214099&Signature=Zysn69urdt83q4~vl0GnxzPC3PccYB~UWAOs~8xiJ9S-EgqIkht5imi6vK2WmWv7sKMZMWFM3kBIleTWQWbU0dH6yGmQ~mVp-YvvX4ZTXk1z0vVsCf070INoecBU3FzP53QSMshs61C3MhJn24AbLiZZkPqa0JeOA0LIyqdgNVQm~nnHpHYxjqz-fyU1~aP8jHewVcjazbTkkcBbUP~Tu7OIv6DXA8Is913l2IRXNcSjTja93mt-i~eCpHCe1Re-QFcj9YYjjjVyu23vB6iB2w8hs~T1~L3PvanBPRZURd5wmCFfxfjW802qE2dQcVZTfNUXvZkn0sTCyC4xX3wnug&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA.

OECD. (2024). *Climate Finance Provided and Mobilised by Developed Countries in 2013-2022*. OECD Publishing. https://www.oecd-ilibrary.org/environment/climate-finance-provided-and-mobilised-by-developed-countries-in-2013-2022_19150727-en.

OECD. (n.d.). Total Flows by Donor (ODA+OOF+Private) [DAC1]. *OECD.Stat*. https://stats.oecd.org/Index.aspx?DataSetCode=Table1.

Pauw, W.P., Moslener, U., Zamarioli, L.H., Amerasinghe, N., Atela, J., Affana, J.P.B., Buchner, B., Klein, R.J.T., Mbeva, K.L., Puri, J., Roberts, J.T., Shawoo, Z., Watson, C., & Weikmans, R. (2022). Post-2025 Climate Finance Target: How Much More and How Much Better? *Climate Policy, 22*(9-10), 1241-1251.

Pleeck, S., & Mitchell, I. (2023, November 15). *The EU's Carbon Border Tax: How Can Developing Countries Respond?* Center For Global Development. https://www.cgdev.org/blog/eus-carbon-border-tax-how-can-developing-countries-respond.

Qian, H., Qi, J., & Gao, X. (2023). What Determines International Climate Finance? Payment Capability, Self-Interests and Political Commitment. *Global Public Policy and Governance, 3*(1), 41-59.

Qi, J., & Qian, H. (2023). Climate Finance at a Crossroads: It is High Time to Use the Global Solution for Global Problems. *Carbon Neutrality, 2*(31), 1-22.

Raghutla, C., & Chittedi, K.R. (2023). The Effect of Technological Innovation and Clean Energy Consumption on Carbon Neutrality in Top Clean Energy-Consuming Countries: A Panel Estimation. *Energy Strategy Reviews, 47*, 1-10.

Richardson, G. (2016). The Determinants of Tax Evasion: A Cross-country Study. In M. Dion, D. Weisstub & J.L. Richet (Eds.), *Financial Crimes: Psychological, Technological, and Ethical Issues* (pp. 33-57). Springer International Publishing. https://link.springer.com/chapter/10.1007/978-3-319-32419-7_2.

Roberts, J.T., & Weikmans, R., Robinson, S.A., Ciplet, D., Khan, M., & Falzon, D. (2021). Rebooting a Failed Promise of Climate Finance. *Nature Climate Change, 11*(3), 180-182.

Shao, X., Zhong, Y., Liu, W., & Li, R.Y.M. (2021). Modeling the Effect of Green Technology Innovation and Renewable Energy on Carbon Neutrality in N-11 Countries? Evidence from Advance Panel Estimations. *Journal of Environmental Management, 296*, 1-10.

Sharma, S., & Hillman, D. (2024). *The Climate Damages Tax: A Guide to What it is and How it Works*. Stamp Out Poverty. https://us.boell.org/sites/default/files/2024-04/cdt_guide_2024_0.pdf.

Shishlov, I., & Censkowsky, P. (2022). Definitions and Accounting of Climate Finance: Between Divergence and Constructive Ambiguity. *Climate Policy, 22*(6), 798–816.

Stadelmann, M., Roberts, J.T., & Michaelowa, A. (2011). New and Additional to What? Assessing Options for Baselines to Assess Climate Finance Pledges. *Climate and Development, 3*(3), 175-192.

Tan, K.C. (2023). Climate Reparations: Why the Polluter Pays Principle is Neither Unfair nor Unreasonable. *Wiley Interdisciplinary Reviews Climate Change, 14*(4), 1-6.

Timperley, J. (2021). The Broken $100-Billion Promise of Climate Finance – and How to Fix it. *Nature, 598*(7881), 400-402.

UN. (1992). *United Nations Framework Convention on Climate Change*. https://unfccc.int/resource/docs/convkp/conveng.pdf.

UNCTAD. (2015). *"New and Additional" Climate Finance: A Continuing Lack of Clarity*. https://unctad.org/system/files/official-document/presspb2015d15_en.pdf.

UNFCCC. (2008). *Kyoto Protocol Reference Manual: On Accounting of Emissions and Assigned Amount*. United Nations. https://unfccc.int/resource/docs/publications/08_unfccc_kp_ref_manual.pdf.

UNFCCC. (2010). *Report of the Conference of the Parties on its Fifteenth Session, Held in Copenhagen from 7 to 19 December 2009*. United Nations. https://unfccc.int/resource/docs/2009/cop15/eng/11a01.pdf#page=4.

UNFCCC. (2011). *Report of the Conference of the Parties on its Sixteenth Session, Held in Cancun from 29 November to 10 December 2010*. United Nations. https://unfccc.int/sites/default/files/resource/docs/2010/cop16/eng/07.pdf?download.

UNFCCC. (2015). *Paris Agreement.* United Nations. https://unfccc.int/sites/default/files/english_paris_agreement.pdf.

UNFCCC. (n.d. a). *Introduction to Climate Finance.* United Nations Climate Change. Retrieved June 3, 2024. https://unfccc.int/topics/introduction-to-climate-finance.

UNFCCC (n.d. b). *Biennial Reports - Data Interface (BR-DI)*. https://www4.unfccc.int/sites/br-di/Pages/InformationDS.aspx.

UNFCCC. (n.d. c). *Greenhouse Gas Inventory Data - Detailed Data by Party*. United Nations Climate Change. https://di.unfccc.int/detailed_data_by_party.

UNFCCC (n.d. d). *Parties & Observers.* United Nations Climate Change. Retrieved June 3, 2024. https://unfccc.int/parties-observers.

Wang, X., & Kockelman, K.M. (2005). Use of Heteroscedastic Ordered Logit Model to Study Severity of Occupant Injury: Distinguishing Effects of Vehicle Weight and Type. *Transportation Research Record, 1908*(1), 195-204.

Weikmans, R., & Roberts, J.T. (2019). The International Climate Finance Accounting Muddle: Is there Hope on the Horizon? *Climate and Development, 11*(2), 97-111.

Wolf, C., & Best, H. (2015). Linear Regression. In H. Best & C. Wolf (Eds.), *The Sage Handbook of Regression Analysis and Causal Inference* (pp. 57-81). Sage Publications. http://ndl.ethernet.edu.et/bitstream/123456789/26799/1/122.Henning%20Best%2C%20Christof%20Wolf-.pdf#page=338.

World Bank. (n.d. a). GDP Per Capita (Constant 2015 US$). *World Bank Group Data.* https://data.worldbank.org/indicator/NY.GDP.PCAP.KD?end=2020&most_recent_year_desc=true&start=2011.

World Bank. (n.d. b). GDP Growth (Annual %). *World Bank Group Data.* https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG.

World Bank. (n.d. c). CO2 Emissions (Metric Tons Per Capita). *World Bank Group Data.* https://data.worldbank.org/indicator/EN.ATM.CO2E.PC.

Zagema, B., Kowalzig, J., Walsh, L., Hattle, A., Roy, C., Dejgaard, H.P. (2023). *Climate Finance Shadow Report 2023: Assessing the Delivery of the $100 Billion Commitment*. Oxfam International. https://oxfamilibrary.openrepository.com/bitstream/handle/10546/621500/bp-climate-finance-shadow-report-050623-en.pdf;jsessionid=CE6481888AA1F5B99FEB3A8634FC1DC6?sequence=19.

Zhang, M., Zhang, D., & Xie, T. (2023). Technology Innovations and Carbon Neutrality in Technologically Advanced Economies: Imperative Agenda for COP26. *Economic Research-Ekonomska Istraživanja, 36*(2), 1-24.

Zhang, W., & Pan, X. (2016). Study on the Demand of Climate Finance for Developing Countries Based on Submitted INDC. *Advances in Climate Change Research, 7*(1-2), 99-104.

Appendices

Appendix A. Calculation of new and additional climate finance

This appendix outlines the calculations used to determine the dependent variable, specifically the percentage of new and additional climate finance provided by Annex-II Parties between 2011 and 2020.

To determine the share of new and additional climate finance for 23 Annex-II Parties from 2011 to 2020, first each donor country's development finance provision in 2009 and their climate finance provision for each respective year were calculated. Hattle et al. (2023) determined the amount of climate finance, for each year, that was considered new and additional compared to a country's development finance distribution in 2009. This was then used to compute the percentage of new and additional climate finance.

The methodology of Hattle et al. (2023) was used to calculate both the total amount of development finance disbursed in 2009 and the total amount of climate finance provided by each country at each respective year. Hattle et al. (2023) did not provide exact figures for the total development finance disbursed by each country in 2009; instead they presented a graph with a line representing the development finance disbursed by each country in 2009, making it difficult to determine exact amounts. Furthermore, although Hattle et al. (2023) provided the total amount of climate finance provided by each country for each year, they did not provide detailed breakdowns of the components. Therefore, recalculations were carried out to ensure accuracy and consistency with Hattle et al.'s (2023) findings.

For example, to calculate the share of new and additional climate finance of Australia in 2013, the following steps were undertaken:

1) **Calculating the total development finance disbursed in 2009** (OECD, n.d.).

- Bilateral Official Development Assistance: $2,311.78 million
- Multilateral Official Development Assistance: $449.83 million
- Other Official Flows: $373.95 million

Total development finance provided in 2009 by Australia: $2,311.78 million + $449.83 million + $373.95 million USD = $3,135.56 million

2) **Determining the reported climate finance in 2013** (UNFCCC, n.d. b). Data is extracted from the second biennial report of Annex-II Parties.

- Total contributions through multilateral channels – climate specific:
  - Mitigation: $12.26 million USD
  - Adaptation: $19.58 million USD
  - Cross-cutting: $5.80 million USD
  - Other: NA
- Total contributions through bilateral, regional and other channels – climate-specific:
  - Mitigation: $38.32 million USD
  - Adaptation: $44.56 million USD
  - Cross-cutting: $115.83 million USD
  - Other: -

Total reported climate finance provided by Australia in 2013: $12.26 million + $19.58 million + $5.80 million + $38.32 million + $44.56 million + $115.83 million = $236.35 million

3) **Computing new and additional climate finance in 2013** (Hattle et al., 2023)
Both the total development finance disbursed in 2009 and the reported climate finance in 2013 aligned with the findings of Hattle et al. (2023), although they used rounded figures. Therefore, the amount of (weak) new and additional climate finance in 2013 by Hattle et al. (2023) could be adopted.

- Weak new and additional climate finance in 2013: $236 million

Percentage of new and additional climate finance provided by Australia in 2013: ($236 million USD / $236 million) x 100 = 100%

Appendix B. New and additional climate finance provision 2011-2020

Table 4

New and additional climate finance provision by Annex-II Parties between 2011 and 2020 (in percentage)

	Percentage new and additional climate finance									
Donor country	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
Australia	100	100	100	100	100	100	99.07	99.24	45.26	53.77
Austria	0	0	42.20	87.92	73.15	100	61.02	6.80	46.05	74.43
Belgium	100	0	0	0	0	8.78	0	0	0	0
Canada	100	99.15	100	100	100	0	73.32	94.87	91.84	100.00
Denmark	62.37	0	39.73	61.27	0	0	0	0	0	0
Finland	100	19.48	100	100	0	0	0	0	0	0
France	21.06	3.17	6.91	2.94	0	0	0	3.66	0	54.40
Germany	85.48	36.64	74.80	100	70.37	96.18	83.96	79.64	94.49	96.39
Greece	0	0	0	0	0	0	0	0	0	0
Iceland	0	0	0	27.27	41.67	100	100	100	100	100.00
Ireland	0	0	0	0	0	0	0	0	0	0
Italy	100	18.34	41.55	100	100	100	100	99.11	99.62	100.00
Japan	38.26	27.13	23.63	0.19	0	8.45	19.50	5.23	21.28	41.03
Luxembourg	17.07	10	46.34	33.33	56.84	61.18	73.81	100	100	100.00
The Netherlands	0	0	0	0	0	0	0	0	0	0
New Zealand	100	100	100	100	100	100	100	98.08	100	100.00
Norway	100	72.49	100	95.99	34.82	57.95	7.31	50.47	37.74	24.93
Portugal	100	100	0	0	0	0	0	0	0	0

Spain	0.19	0	31.00	0	0.32	10.96	9.39	18.02	0	0
Sweden	100	100	100	100	98.30	59.45	100	100	75.32	100.00
Switzerland	100	100	100	100	100	100	100	100	100	100.00
The United Kingdom	100	100	100	100	100	100	100	100	100	100.00
The United States	96.30	98.44	72.28	87.31	100	84.66	85.79	73.74	100	78.86

Note. Based on data obtained from "Total Flows by Donor (ODA+OOF+Private) [DAC1]", by OECD, n.d.; "Biennial Reports - Data Interface (BR-DI)", by UNFCCC, n.d. b; "Seeing Double: Decoding the 'Additionality' of Climate Finance", by A. Hattle, J. Nordbo, A. Myrup, L. Elming, R.B. Sørensen, I. Achton, A.B. Knudsen, E. Bentsen, L.P. Nygaard, C. Mattson, and M. Hansen, 2023.

Appendix C. Correlations between WGIs

Table 5 presents the pairwise correlations between the six Worldwide Governance Indicators (WGIs) of the World Bank. This correlation matrix is intended to examine potential multicollinearity issues among the indicators.

Table 5

Pairwise correlations between WGI variables

	(1)	(2)	(3)	(4)	(5)	(6)
(1) Voice and accountability	1.00					
(2) Political stability and absence of violence/ terrorism	0.75***	1.00				
(3) Government effectiveness	0.83***	0.70***	1.00			
(4) Regulatory quality	0.83***	0.63***	0.87***	1.00		
(5) Rule of law	0.86***	0.70***	0.95***	0.90***	1.00	
(6) Control of corruption	0.90***	0.73***	0.93***	0.90***	0.95***	1.00

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix D. Model selection

This appendix presents the results of the additional models tested to determine the most appropriate approach for analysing the dependent variable, including the fixed-effects model and the binary logistic regression model. Furthermore, Figure 3 illustrates the non-normal distribution of the continuous dependent variable.

Table 6

Fixed-effects model

	Dependent variable: NACF		
	Model 1	*Model 2*	*Model 3*
Log (GDP per capita)	-2.2764***	-1.9557**	-1.7960**
	(0.7077)	(0.8310)	(0.6511)
GDP growth (%)	-0.0056	-0.0012	0.0054
	(0.0077)	(0.0051)	(0.0061)
Government debt (% of GDP)	-1.2499***	-0.7738**	-0.6620**
	(0.3157)	(0.2924)	(0.2630)
Unemployment (% of civilian labour force)	-1.7432	-0.8231	-1.5109
	(1.6646)	(1.3343)	(1.4568)
Share of green votes	-0.0111	-0.0014	-0.0004
	(0.0085)	(0.0077)	(0.0080)
Cabinet composition	0.0093	-0.0020	-0.0037
	(0.0149)	(0.0136)	(0.0120)
GHG evolution (% to 1990)	0.9606	1.5126**	1.7574**
	(0.7120)	(0.6783)	(0.7906)
Log (IEAS)	0.0886	-0.3416	0.5354
	(0.5682)	(0.5489)	(0.5422)
GHG per capita	-0.1357***	-0.1262***	-0.1471***
	(0.0300)	(0.0318)	(0.0400)
Log (Total ODA)		0.6784***	0.7678***
		(0.2116)	(0.2029)
Average WGI		-0.0133	-0.3473
		(0.3537)	(0.4126)
Vulnerability		3.3779	1.0306
		(11.9803)	(11.2679)
Constant	25.8022***	17.4226	11.0326
	(6.8549)	(10.9092)	(8.1846)
Year fixed effects	NO	NO	YES
Observations	230	230	230
Number of countries	23	23	23
R-squared	0.2167	0.3649	0.4258

Note. Standard errors are clustered at country level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 3

Normal distribution of the continuous dependent variable

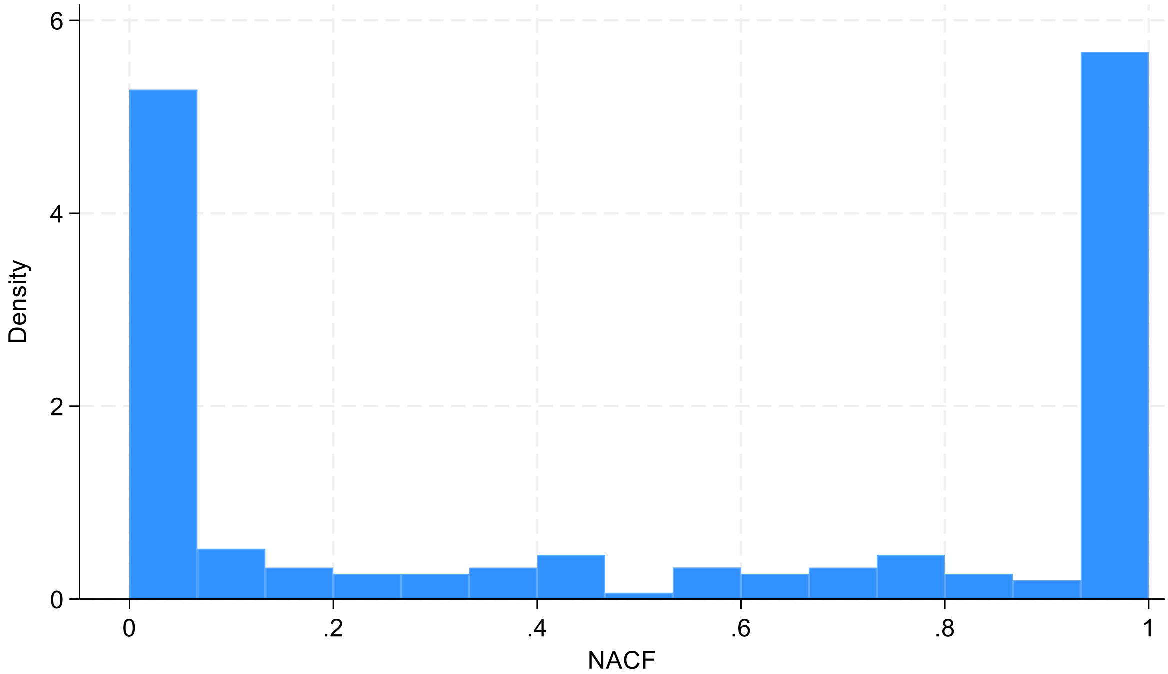


Table 7

Binary logistic regression model

	Dependent variable: NACF		
	Model 1	*Model 2*	*Model 3*
Log (GDP per capita)	1.4628**	0.8765	10.1207
	(0.7081)	(1.1000)	(78.9347)
GDP growth (%)	-0.1516***	-0.1792**	-0.0698
	(0.0569)	(0.0764)	(0.4603)
Government debt (% of GDP)	-0.3957	-0.5940	1.5496
	(0.4102)	(0.5481)	(15.6980)
Unemployment (% of civilian labour force)	-12.7626***	-19.8402***	28.6292
	(4.5789)	(6.7904)	(84.0762)
Share of green votes	-0.0480	0.0249	0.6400
	(0.0411)	(0.0592)	(0.8752)
Cabinet composition	-0.1647	-0.0318	-0.7956**
	(0.1279)	(0.1445)	(0.3869)
GHG evolution (% to 1990)	3.9604***	5.6570***	58.2186***
	(1.0820)	(1.6667)	(21.8579)
Log (IEAS)	1.7897***	-2.1006*	15.3851
	(0.6046)	(1.1717)	(63.3461)
GHG per capita	0.0150	0.0563	2.7639
	(0.0463)	(0.0756)	(3.9993)
Log (Total ODA)		1.1833***	25.4785
		(0.2434)	(19.3793)
Average WGI		-1.7033**	-6.7008
		(0.7913)	(12.4456)
Vulnerability		-39.9852***	-280.6443
		(10.0775)	(246.8216)
Constant	-27.0488***	5.9726	-385.8435
	(9.5077)	(14.6522)	(1,006.2603)
Year fixed effects	NO	NO	YES
Country fixed effects	NO	NO	YES
Observations	230	230	100
Number of countries	23	23	9
R-squared	0.1890	0.3586	0.6940

Note. Robust standard errors are in parentheses below the coefficients.
*** p<0.01, ** p<0.05, * p<0.1

Appendix E. Testing statistical assumptions

This appendix presents the results of testing the statistical assumptions for conducting an ordered logistic regression with fixed-effects. These assumptions include multicollinearity, proportional odds, autocorrelation, and homoscedasticity.

Table 8

Pairwise correlations between all variables (N = 230)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) NACF	1.00													
(2) Log (GDP per capita)	0.32***	1.00												
(3) GDP growth	0.03	0.33***	1.00											
(4) Government debt	-0.35***	-0.67***	-0.28***	1.00										
(5) Unemployment	-0.37***	-0.66***	-0.23***	0.37***	1.00									
(6) Green votes	0.22***	0.48***	0.09	-0.46***	-0.44***	1.00								
(7) Cabinet composition	-0.08	-0.10	-0.11*	-0.09	0.15**	0.06	1.00							
(8) GHG evolution	0.03	-0.08	0.22***	0.07	0.08	0.08	-0.15**	1.00						
(9) Log (IEAS)	0.09	0.08	-0.12*	-0.14**	-0.15**	-0.24***	-0.01	-0.50***	1.00					
(10) GHG per capita	0.19***	0.39***	0.16**	-0.15**	-0.24***	0.10	-0.21***	0.28***	0.06	1.00				
(11) Log (GHG emissions)	0.13**	-0.27***	-0.09	0.38***	0.02	-0.49***	-0.27***	-0.05	0.55***	0.32***	1.00			
(12) Log (ODA)	0.24***	0.11*	-0.06	0.02	-0.25***	-0.36***	-0.19***	-0.43***	0.79***	0.17***	0.80***	1.00		
(13) WGI	0.28***	0.73***	0.31***	-0.70***	-0.72***	0.51***	-0.12*	0.00	0.05	0.24***	-0.29***	0.06	1.00	
(14) Vulnerability	-0.43***	-0.47***	-0.12*	0.62***	0.16**	-0.30***	0.01	0.05	-0.18***	0.05	0.23***	-0.04	-0.40***	1.00

*** p<0.01, ** p<0.05, * p<0.1

Table 9

Multicollinearity assumption

Variable	**VIF**
Log (ODA)	25.48
Log (GHG emissions)	24.3
Log (GDP per capita)	7.46
WGI	4.93
Government ebt	3.72
Log (IEAS)	3.62
Unemployment	3.55
GHG per capita	3.53
GHG evolution	2.92
Green votes	2.22
Vulnerability	2.05
GDP growth	1.34
Cabinet composition	1.29
Mean VIF	6.64

Table 10

Multicollinearity assumption, excluding GHG emissions

Variable	**VIF**
Log (ODA)	4.32
Log (GDP per capita)	4.02
WGI	3.97
Government debt	3.60
Log (IEAS)	3.54
Unemployment	3.41
Green votes	2.15
Vulnerability	2.03
GHG evolution	1.91
GHG per capita	1.78
GDP growth	1.29
Cabinet composition	1.23
Mean VIF	2.77

Table 11

Proportional odds assumption

	Chi^2	p > Chi^2
All	73.92	0.000
Log (GDP per capita)	16.12	0.000
GDP growth	4.51	0.105
Government debt	9.84	0.007
Unemployment	32.09	0.000
Green votes	1.29	0.525
Cabinet composition	5.50	0.064
GHG evolution	8.35	0.015
Log (IEAS)	8.74	0.013
GHG per capita	3.32	0.191
Log (ODA)	1.22	0.543
WGI	3.48	0.176
Vulnerability	0.96	0. 618

Figure 4

Breusch-Pagan Lagrange Multiplier test results

```
Breusch-Pagan LM test of independence: chi2(253) =   393.408, Pr = 0.0000
Based on 10 complete observations over panel units
```

Figure 5

Modified Wald test results

```
. xttest3

Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (23)  =      570.35
Prob>chi2 =      0.0000
```

Appendix F. Marginal effects

Table 12

Marginal effects of all variables

	Dependent variable: NACF			
	1	2	3	4
Log (GDP per capita)	2.529847***	.6175174*	.2253061	-3.372671**
GDP growth (%)	-.004311	-.0010523	-.0003839	.0057472
Government debt	.2616271*	.0638613*	.0233003	-.3487887**
Unemployment	2.55801**	.6243918	.2278142	-3.410216**
Green votes	.002166	.0005287	.0001929	-.0028876
Cabinet composition	.0145948	.0035625	.0012998	-.0194571
GHG evolution	-1.680549***	-.3858006*	-.1407624	2.107112***
Log (IEAS)	-1.979788**	1.4832519	-.1763182	2639358**
GHG per capita	.0897869***	.0219163*	.0079963	-.1196996***
Log (ODA)	-.4935851***	-.1204805*	-.0439583	.6580239***
Average WGI	.2662114	.0649803	.0237086	-.3549003
Vulnerability	-1.658416	-.4048072	-.1476971	2.21092

*** p<0.01, ** p<0.05, * p<0.1

Appendix G. Syntax

```
// Data preparation

// Installation of outreg2, asdoc, xttest2, xttest3
ssc install outreg2

ssc install asdoc

ssc install xttest2

ssc install xttest3

// Rename variables
rename(*), lower

// Recode some variables
encode country, gen(country2)

// Take logs
gen ln_gdpcapita = ln(gdpcapita)
gen ln_ieas = ln(ieas)
gen ln_ghgemissions = ln(ghgemissions)
gen ln_oda = ln(oda)

// Correlation WGIs
asdoc pwcorr va ps ge rq rl cc, save(correlationstable) star(all) dec(2) replace

// Take mean of 6 WGIs
egen wgi = rowmean(va ps ge rq rl cc)

// Create ordinal variable
xtile nacf2 = nacf, nquantiles(4)

// Create binary variable
gen nacf3 = 0
replace nacf3 = 1 if nacf > 0
```

```
save gk_final_data, replace
*--------------------------------------------------------------------------*

// Load data
use gk_final_data, clear
describe

// Set panel data
xtset country2 year
xtline nacf     //

// Descriptives
sum gdpcapita gdpgrowth govdebt unemp greenvotes ghgevolution          ///
    ieas ghgcapita oda wgi vuln

tab nacf2

tab govcomp

// Correlations
asdoc pwcorr nacf ln_gdpcapita gdpgrowth govdebt unemp greenvotes govcomp  ///
    ghgevolution ln_ieas ghgcapita ln_oda wgi vuln,    ///
         save(correlationstable) star(all) dec(2) replace

// Assumptions ordered logit model
reg nacf2 ln_gdpcapita gdpgrowth govdebt unemp greenvotes govcomp       ///
   ghgevolution ln_ieas ghgcapita ln_ghgemissions ln_oda vuln wgi, r
vif

reg nacf2 ln_gdpcapita gdpgrowth govdebt unemp greenvotes govcomp       ///
   ghgevolution ln_ieas ghgcapita ln_oda vuln wgi, r
vif

ologit nacf2 ln_gdpcapita gdpgrowth govdebt unemp greenvotes govcomp       ///
    ghgevolution ln_ieas ghgcapita ln_oda vuln wgi, r
brant
```

```
// Assumptions fixed-effects
xtreg nacf ln_gdpcapita gdpgrowth govdebt unemp greenvotes govcomp        ///
    ghgevolution ln_ieas ghgcapita ln_oda vuln wgi        ///
        i.year, fe cluster(country2)
xttest2

xtreg nacf ln_gdpcapita gdpgrowth govdebt unemp greenvotes govcomp        ///
    ghgevolution ln_ieas ghgcapita ln_oda vuln wgi        ///
        i.year, fe cluster(country2)
xttest3

*---------------------------------------------------------------------------*

// Fixed or Random effects model (Hausman Test)
xtreg nacf ln_gdpcapita gdpgrowth govdebt unemp greenvotes govcomp        ///
    ghgevolution ln_ieas ghgcapita ln_ghgemissions ln_oda vuln wgi        ///
        i.year, fe
estimates store fixed

xtreg nacf ln_gdpcapita gdpgrowth govdebt unemp greenvotes govcomp        ///
    ghgevolution ln_ieas ghgcapita ln_ghgemissions ln_oda vuln wgi        ///
        i.year, re
estimates store random

hausman fixed random, sigmamore
outreg2 utreg2 using hausman.doc, replace ctitle(Hausman) dec(4)

*---------------------------------------------------------------------------*

// Fixed effects model
xtreg nacf ln_gdpcapita gdpgrowth govdebt unemp greenvotes govcomp        ///
    ghgevolution ln_ieas ghgcapita, fe cluster(country2)
outreg2 utreg2 using fixed_effects.doc, replace ctitle(Model 1)  ///
     addtext(Year fixed effects, YES) dec(4)

xtreg nacf ln_gdpcapita gdpgrowth govdebt unemp greenvotes govcomp        ///
```

```
    ghgevolution ln_ieas ghgcapita ln_oda vuln wgi, fe cluster(country2)
outreg2 utreg2 using fixed_effects.doc, append ctitle(Model 2)   ///
     addtext(Year fixed effects, YES) dec(4)

xtreg nacf ln_gdpcapita gdpgrowth govdebt unemp greenvotes govcomp        ///
    ghgevolution ln_ieas ghgcapita ln_oda vuln wgi       ///
         i.year, fe cluster(country2)
outreg2 utreg2 using fixed_effects.doc, append ctitle(Model 3)   ///
     addtext(Year fixed effects, YES) dec(4)

// Binary logit model
logit nacf3 ln_gdpcapita gdpgrowth govdebt unemp greenvotes govcomp        ///
    ghgevolution ln_ieas ghgcapita, r
outreg2 utreg2 using logit_model.doc, replace ctitle(Model 1)   ///
     addtext(Year fixed effects, NO) dec(4)

logit nacf3 ln_gdpcapita gdpgrowth govdebt unemp greenvotes govcomp        ///
    ghgevolution ln_ieas ghgcapita ln_oda vuln wgi, r
outreg2 utreg2 using logit_model.doc, append ctitle(Model 2)   ///
     addtext(Year fixed effects, NO) dec(4)

logit nacf3 ln_gdpcapita gdpgrowth govdebt unemp greenvotes govcomp        ///
    ghgevolution ln_ieas ghgcapita ln_oda vuln wgi       ///
         i.year i.country2, r
outreg2 utreg2 using logit_model.doc, append ctitle(Model 3)   ///
     addtext(Year fixed effects, YES) dec(4)

// Ordered logit model
ologit nacf2 ln_gdpcapita gdpgrowth govdebt unemp greenvotes govcomp        ///
    ghgevolution ln_ieas ghgcapita, r
outreg2 utreg2 using ologit_model.doc, replace ctitle(Model 1)   ///
     addtext(Year fixed effects, NO) dec(4)

ologit nacf2 ln_gdpcapita gdpgrowth govdebt unemp greenvotes govcomp        ///
    ghgevolution ln_ieas ghgcapita ln_oda vuln wgi, r
outreg2 utreg2 using ologit_model.doc, append ctitle(Model 2)   ///
```

```
    addtext(Year fixed effects, NO) dec(4)

ologit nacf2 ln_gdpcapita gdpgrowth govdebt unemp greenvotes govcomp     ///
    ghgevolution ln_ieas ghgcapita ln_oda vuln wgi     ///
        i.year i.country2, r
outreg2 utreg2 using ologit_model.doc, append ctitle(Model 3)  ///
    addtext(Year fixed effects, YES) dec(4)

*---------------------------------------------------------------------------*

// Marginal effects
margins, dydx(*)
```