Climate Finance and the Diffusion of Local Inclusion Norms
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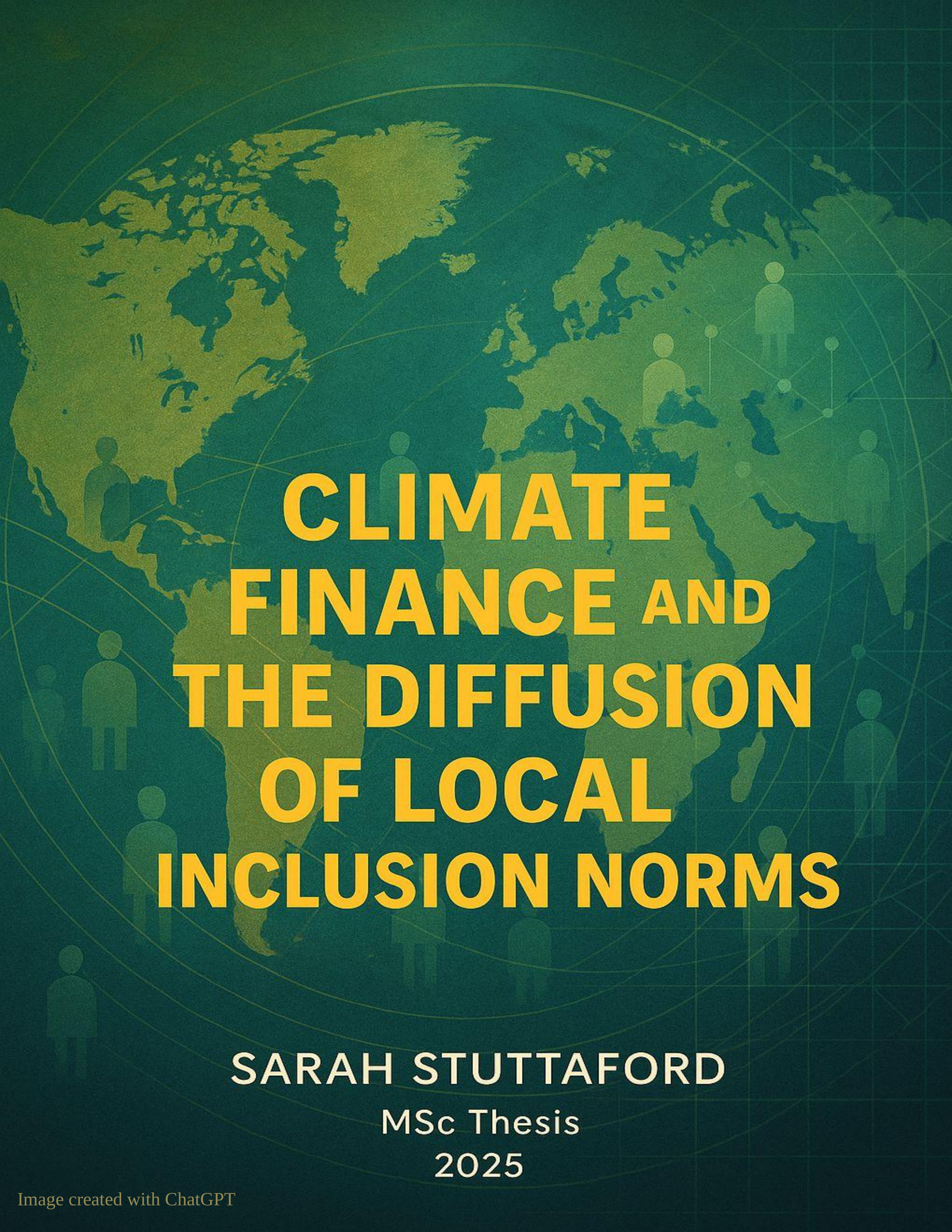

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This thesis is submitted in partial fulfillment of the requirements of the Advanced Master of Science in International Relations and Diplomacy, Leiden University

Climate Finance and the Diffusion of Local Inclusion Norms

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21 May 2025

Word Count (incl. references and excl. appendix, abstract, and acknowledgements): 22,105

I would like to thank my family, friends, partner, and professors for all their support throughout this process and for keeping me motivated.

Abstract

The Adaptation Fund (AF) and Green Climate Fund (GCF) are two multilateral climate funds working to alleviate the complexity of climate finance and improve financial flows with direct-access entities. Direct-access entities allow national and subnational organizations to receive funding directly, bypassing intermediaries and addressing community needs in mitigation and adaptation projects. Numerous studies show that local inclusion improves the effectiveness of climate finance, but little research focuses on the sentiment of local inclusion in project implementation of different multilateral climate funds. As a result, this thesis poses the following question: *How does the type of implementing entity impact the sentiment surrounding local inclusion rhetoric in multilateral climate funds' project implementation?* Norm diffusion theory expects that international implementing entities will express more positive sentiment towards local inclusion rhetoric than direct-access and regional entities to fulfill the local inclusion norm. This norm encourages international implementing entities to present themselves as more inclusive due to previous criticism from non-state actors for neglecting stakeholders in development projects. International implementing entities, however, are likely to exploit this norm, presenting themselves as facilitators of inclusion even if this is not the case. As direct-access entities are often assumed to be local, this locality is expected to allow them more flexibility in their perceived sentiment towards local inclusion rhetoric. Sentiment analysis of the project documents from the AF and GCF and the subsequent multiple Ordinary Least Squares (OLS) regressions instead offered two novel contributions to the field of climate finance and climate justice: 1) International implementing entities can diffuse the local inclusion norm in the weaker structured AF and 2) the GCF, with stronger fiduciary management, financial capacity, technical expertise, and strict project document structures, can counter international implementing entities acting as norm entrepreneurs themselves. Understanding how different implementing entities and multilateral climate funds impact sentiment surrounding local inclusion rhetoric helps reveal the underlying power dynamics which obscure or support local inclusion in equitable climate finance.

Keywords: Local inclusion, direct-access entities, multilateral climate funds, norm diffusion, international implementing entities

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List of Abbreviations

AF	Adaptation Fund
BP	Breusch-Pagan
COP	Conference of Parties
DF	Degrees of Coefficient
GCF	Green Climate Fund
GVIF	Generalized Variance Inflation Factor
IGO	Inter-Governmental Organization
IO	International Organization
KWIC	Key Words in Context
MCF	Multilateral Climate Fund
MENA	Middle East North Africa
NGO	Non-Governmental Organization
OLS	Ordinary Least Squares
UN	United Nations
UNDP	United Nations Development Program
UNFCCC	United Nations Framework Convention on Climate Change
UPCRA	Unidad Para Cambio Rural Argentina
VIF	Variance Inflation Factor
WFP	World Food Program

Introduction

As global temperatures are set to surpass the Paris Agreement threshold of 1.5°C to 3.1°C by 2100, the pressure for historical emitters to financially contribute to countries most vulnerable to climate change is mounting. At the recent COP29, countries led by China and India called on these historical emitters to contribute $1.3 trillion annually, which pales in comparison to the annual $300 billion developed countries agreed to pledge until 2035 (Abnett et al., 2024). This type of financing, known as climate finance, was first internationally recognized with the Copenhagen Accord in 2010, where developed countries agreed to mobilize $100 billion per year by 2020 to lower greenhouse gas emissions and improve climate resilience (Basak & Karlsson-Vinkhuyzen, 2022, pp. 135-40). The gap between financial expectations and contributions has invited a range of actors to participate in the climate finance landscape according to their vested interests. They include international organizations (IOs), multilateral development banks, national governments, civil society, and the private sector. At the same time, climate financial mechanisms include tax credits, green bonds, target lending, multilateral funding, and feed-in-tariffs (Bracking & Leffel, 2021, p. 7; Bhandary et al., 2021, p. 529). This polycentric structure complicates the tracking of financial flows from contributing entities to intermediaries and the ultimate beneficiaries.

To alleviate the complexity of the climate finance regime, several scholars (Caldwell & Larsen, 2021; Müller & Bhandary, 2022; Colenbrander et al., 2018; Browne, 2022) advocate for a more inclusive funding modality known as direct-access. Direct-access entities are subnational, national, or occasionally regional, entities in developing countries, including development banks, government ministries, private banks, and NGOs. They can apply for accreditation to receive funding from multilateral climate finance funds (MCFs) directly once nominated by a designated authority, normally a government agency from within the country (Mathur-Filipp & Bista, 2015; Green Climate Fund, 2011). Direct-access is important for devolving decision-making locally. Local-level inclusion in climate finance ensures community needs are directly addressed as local actors and governments are often the best equipped to connect with beneficiaries, enhancing the decision-making of marginalized groups and counteracting social exclusion (Möller, 2019). Involving local stakeholders ensures adaptation and mitigation projects are implemented effectively, as there is a stronger understanding of potential risks and challenges due to existing power asymmetries or governance dynamics (Ogunyiola et al., 2021; Chu et al., 2016; Bertilsson

& Soneryd, 2023). Innovation combined with local knowledge creates sustainable solutions to improve livelihood opportunities, as seen in India, for example, where the Self-Employed Women's Association developed a heat index for insurance where payouts are automatically triggered when temperatures are too high to work outside (Zetterli et al., 2025). Direct-access can, therefore, create sustainable and low-cost solutions as project objectives are tailored to the needs of community members.

Most climate finance disbursed, however, does not emphasize community needs in the same manner as direct-access entities. From 2017 to 2021, only 17% of adaptation climate finance directly targeted local communities (United Nations Environment Program, 2023, p. 46). Entities' local knowledge is important to address the needs of communities in project implementation, whereas international entities tend to prioritize donor interests (Fenton et al., 2014; Price, 2021). Despite the assumed benefits of improved representation and inclusive decision-making through direct-access, assessing how these commitments to local inclusion are reflected in project implementation is largely absent from the literature. Some scholars (Omukuti, 2020; Price, 2021; Kuhl & Shinn, 2022; Omukuti et al., 2022) use interviews and qualitative document analyses to highlight the flaws in assuming these entities will easily translate to more inclusive climate finance practices. The norm of local inclusion also sets a dangerous precedent for international implementing entities, where IOs, typically in development aid, exaggerate the positive aspects and successes of inclusion over the failures to compensate for the decades of failing to engage and include stakeholders equitably (Browne, 2022; Babb & Kentikelenis, 2018). The impact of implementing entity type on the perception of local inclusion could reveal how different norms of local inclusion, the assumption of locality with direct-access entities and the exaggeration of locality with international entities, obscure or confirm which actors genuinely engage and participate in project implementation. Understanding this relationship between implementing entities and the perception of local inclusion quantitatively across multiple multilateral funds, however, remains severely understudied.

Due to the gap in research methodology and the puzzle of assessing local inclusion in climate finance, I pose the following research question: *How does the type of implementing entity impact the sentiment surrounding local inclusion rhetoric in multilateral climate funds' project implementation?* To analyze how the type of implementing agency impacts the sentiment of local inclusion rhetoric, the project documents, including final evaluation reports and annual project summaries, from two MCFs, the Adaptation Fund (AF) and Green Climate Fund (GCF), will be studied. Understanding how entities with varying power impact sentiment surrounding local inclusion rhetoric can reveal the extent to which implementing entities can criticize existing MCF's practices or use MCFs to diffuse norms in climate finance. As climate finance is a rapidly growing field, up-to-date research is of the utmost importance to understand how MCFs and implementing entities' practices of disbursement shift as the scale of funding mobilization increases. Using the theory of norm diffusion, the sentiment analysis and following multiple OLS regressions, which compare how national direct-access, regional, and international implementing entities impact sentiment surrounding local inclusion rhetoric, offers two novels contributions: 1) International implementing entities can diffuse the exploited local inclusion norm in the weaker structured AF, and 2) the GCF, with stronger fiduciary management, financial capacity, technical expertise, and strict project document structure can counter international implementing entities acting as norm entrepreneurs themselves. These findings, therefore, demonstrate how implementing entities and MCFs with different sources of power can conflict with or support norms of local inclusion.

Academically, this thesis fills a methodological gap as the existing literature struggles to assess MCFs' commitments to local inclusion norms. Rather than measuring local inclusion itself, the perceived sentiment of local inclusion reveals which stakeholders hold the most influence in project implementation to portray their work and reputation in a more positive light. This influence can be displayed in different forms of power, discussed below in the literature, such as the experience and institutional capacity of implementing entities. In the case of the AF, the results find that international implementing entities do impact sentiment more positively than direct-access entities, emphasizing their penchant for 'cheap talk' in project implementation, as positive sentiment surrounding local inclusion rhetoric does not guarantee genuine local inclusion. Uncovering these power dynamics in climate finance also contributes to existing theories on norm consumption and diffusion of implementing entities and MCFs, which are often neglected in norm life cycle theory (Martin and Simmons, 2012). With the case of the GCF, the results find no implementing entities significantly impact sentiment surrounding local inclusion rhetoric, contradicting the behavioral expectations of implementing entities derived from norm diffusion theory. Instead, these findings suggest the robust structure of the GCF, in comparison to the AF, allows it to resist norm diffusion from more influential international implementing entities. Acting as a norm entrepreneur itself, the GCF can distill a reinterpreted local inclusion norm that favors its own reputation rather than advance the agenda of international implementing entities.

These research findings also hold policy relevance and societal significance. Understanding the actors responsible for the diffusion of local inclusion norms and the prevalence of positive or negative sentiment urges policymakers and practitioners to build more objective frameworks when assessing the success of adaptation and mitigation projects in climate finance. These lessons learned from the relationship between entity type and sentiment surrounding local inclusion can also be implemented to operationalize future multilateral funds, such as COP27's Loss and Damage Fund (United Nations Climate Change, 2025).

This thesis starts with an overview of the existing climate finance literature in Chapter 1, focusing on the local inclusion norm in the context of institutional innovations and vulnerability. Next, the theoretical framework of norm diffusion in IOs is applied to the research question in Chapter 2. Chapter 3 justifies the case selection of the AF and GCF alongside the selected methodology of sentiment analysis and multiple OLS regressions. Chapter 4 presents the results of the multiple OLS regressions, while Chapter 5 discusses and interprets the OLS regressions' findings, drawing on most-similar case comparisons for further analysis. In Chapter 6, the relevant academic and societal implications drawn from the quantitative analysis are examined in the context of existing theories, emphasizing the importance of meaningful local inclusion and what it can look like in climate finance.

Chapter 1: Literature Review

1.1 Direct-Access Entities and Institutional Innovations

The field of climate finance literature regarding MCFs focuses predominantly on two issue areas: institutional innovations and vulnerability. MCFs are presented as innovative financing mechanisms engaging with the private sector, encouraging equal donor and recipient representation on the board, and participating with civil society. Direct-access, however, is one of the more well-researched innovations, capturing academics' interest. While direct-access is not exclusive to climate finance, MCFs implement it more seriously than traditional development aid structures. The AF, for example, has seen project outcomes increasingly align with domestic concerns, stimulate local innovation, and increase agency in decision-making (Müller & Bhandary, 2022). The GCF also witnessed similar benefits in the pilot phase of its enhanced direct-access program with increased participation of subnational and national actors (Müller & Bhandary, 2022). Improving local actors' decision-making in funding allocation avoids the 'good governance' trap that prioritizes international actors' assumed expertise over local actors' knowledge (Browne, 2022). If local actors are excluded from climate finance funding, mitigation and adaptation projects risk reinforcing existing inequalities and further marginalization of the most vulnerable populations (Colenbrander et al., 2018). Despite the positive praise direct-access entities receive, this funding modality risks ticking donor checklists of inclusion rather than facilitating tangible participation and representation.

Improving the representation of local actors through national and subnational entities does not immediately translate to holistic inclusion in climate financing. National ministries, for example, can qualify as accredited direct-access entities, able to enforce their political agenda over community needs and concerns (Alcañiz & Giraudy, 2023). In a Global Environment Facility Project in Tanzania, government control of adaptation finance created a hierarchy in funding and project-design decision-making where community groups and organizations' voices carried the least weight (Omukuti, 2020). Country ownership principles can still risk reproducing local injustices and marginalized communities as the interests and power of national and subnational actors clash (Alcañiz & Giraudy, 2023). Direct-access entities do not always or consistently address community outcomes in climate finance projects (Price, 2021), allowing the normative assumption of direct-access entities' local status to ensconce further marginalization. Therefore, while this funding modality can lead to increased local inclusion, it is not guaranteed.

Direct-access entities' shortcomings can also stem from the structure of MCFs and their institutional innovations. Despite readiness-start programs to financially help entities address multilateral funds' accreditation criteria (Bertilsson & Thörn, 2021; Adaptation Fund, 2025b), direct-access entities often still lack the institutional capacity necessary to fulfill donor requirements, designating a significant portion of their funding to do so (Basak & Karlsson-Vinkhuyzen, 2022; Fenton et al., 2014). Projects that prioritize scalability and replicability over local input are also often preferred in the approval process (Kuhl & Shinn, 2022; Chaudury, 2020). One institutional innovation attributed to these MCFs, donor-recipient board parity, can also limit the decision-making of direct-access entities. Equal representation between donors and recipients on MCFs' boards in the context of earmarked funding, for example, appears perfunctory. Earmarking funding allows donors to influence the destination and use of climate finance funds with recipient board members possessing little power to oppose these stipulations (Graham & Serdaru, 2020). While the GCF condones this practice, the AF does not, reducing incentives for donors to contribute to the fund as evidenced by their struggle to mobilize funding to a similar scale as the GCF (Graham & Serdaru, 2020).

Other institutional innovations MCFs are praised for, such as civil society participation and private sector engagement, can also work against direct-access entities' decision-making. The involvement of civil society actors as observers to promote local inclusion during the project approval phase often appears more symbolic than practical. Bertilsson and Soneryd (2023) found that the GCF disregarded Indigenous Groups' concerns of project outcomes and community impact if they clashed with the GCF's interests. Attracting private sector investment in the case of the GCF also encourages different transparency standards as the private sector values confidentiality in funding allocation (Kalinowski, 2024). Private sector engagement can risk financializing climate finance as well, encouraging profit-making goals over the national objectives emphasized in country ownership (Bertilsson & Thörn, 2021). The pervasive power dynamics within the structures of MCFs illustrate the difficulties local actors encounter when trying to meaningfully contribute to project implementation.

1.2 Roles of International and Regional Entities

When analyzing the type of implementing entity in relation to sentiment surrounding local inclusion rhetoric, it is also important to consider the role of international and regional entities.

These entities tend to boast well-established institutional capacity, robust fiduciary management, and transparent reporting (Fenton et al., 2014). Their experience in the field and international track record minimizes reputational costs for multilateral funds as well (Independent Evaluation Unit, 2023). Donors are also less willing to cede authority in decision-making, believing their interests and values will be better guarded in international and regionally recognized entities (Browne, 2022). Despite these strengths, international entities are still subject to several shortcomings. Limited communication between international entities with competing agendas, for example, risks repeating similar project outcomes while marginalizing local actor involvement (Liang & Liu, 2020). International entities also tend to assume apolitical approaches to their funding disbursement which risks aggravating local tensions (Skovgaard et al., 2023). Further, the overhead costs of international intermediaries create a bottleneck where the funding that reaches the ultimate beneficiaries is significantly reduced (Fenton et al., 2014). Literature on international entities reveals that their strengths lie in consistency and accountability, but they risk obfuscating local inclusion in project implementation.

This criticism for disproportionately neglecting stakeholders in practice from non-state actors (Browne, 2022; Babb & Kentikelenis, 2018) convinced prominent international implementing entities, such as the World Bank and UN agencies, to adopt, or at least appear to adopt, more locally inclusive practices with the local inclusion norm. The World Bank invested nearly $85 billion in inclusive development practices in the mid-2000s. Assessing the use of this funding, Mansuri and Rao (2013) found that local participation in development not only improves livelihood opportunities but also supports the decision-making of marginalized groups, but the risk of illegal elite capture is still strong in stratified societies, encouraging the cooperation of a responsive state to monitor and implement project goals. Already in the 1990s, there was a shift among Bretton Woods Institutions to “use local knowledge more effectively” in financial policies (Bird, 1994, p. 500). The UN also sought to change its language and practices. The Sustainable Development Goals, for example, adopted a strong emphasis on inclusion in economic growth, societies, and institutions, language that was starkly absent in the previous Millennium Development Goals (Georgeson & Maslin, 2018). While IOs adopted more inclusive practices in their project implementation, their adoption of these practices often remained rhetorical. External reviews on the management of implementing partners working with the UN system (Bartsiotas & Prom-Jackson, 2013; Achamkulangare, 2021) found that while enhanced local participation was encouraged theoretically, calls for national capacity and inclusive stakeholder management struggled to be realized practically due to local inclusion's ill-defined meaning in development. These IOs, who act as international implementing entities for the AF and GCF, therefore, continue to uphold the local inclusion norm in climate finance to improve their reputation and avoid further criticism from civil society.

1.3 Vulnerability in Climate Finance

As of now, the literature explored focused on qualitative research methods as studies on the implementing entity type and its impact on local inclusion predominantly rely on narrative analysis and interviews, creating a research gap in triangulation. Quantitative research within the climate justice field of climate finance largely focuses on the question of country vulnerability in correlation with allocated climate funding. Countries with low vulnerability and low institutional capacity often struggle to access climate finance funding (Saunders, 2019). Bilateral funding, however, indicates that countries with high physical vulnerability to climate change receive proportionately more adaptation aid from donors compared to countries less vulnerable (Weiler et al., 2018; Betzold & Weiler, 2017; Islam, 2022). Yet Doshi and Garschagen's 2020 study concludes that the institutional capacity of recipient countries is the driving force of adaptation finance rather than vulnerability. Climate justice drives climate finance literature, analyzing how traditional power relations between donor and recipient countries are reflected in the distribution patterns of climate finance (Ciplet et al., 2022). Regression analyses, in climate finance literature, however, focus on country rather than project level analysis (Saunders, 2019; Weiler et al., 2018; Betzold & Weiler, 2017; Islam, 2022; Doshi and Garschagen, 2020). Yet, insights from this literature on climate financing disbursement can still help inform how country governance and stability influence the sentiment surrounding local inclusion in project implementation.

1.4 Research Gap

Climate finance literature engages in climate justice narratives to understand how power relations are reproduced in project approval and implementation stages. The existing literature suggests that direct-access, regional, and international entities all encourage different levels of local inclusion, restricted or empowered by institutional norms and barriers. The impact of the type of implementing entity on the perceived sentiment of local inclusion, however, is largely absent from the literature. While studies assess MCFs' commitment to local inclusion (Omukuti et al., 2022), they do so qualitatively through interviews, predominantly focusing on a single multilateral fund from a policy framework perspective. Existing quantitative assessments to understand inclusion also focus on country vulnerability in relation to funding allocation (Saunders, 2019; Weiler et al., 2018; Betzold & Weiler, 2017; Islam, 2022; Doshi & Garschagen, 2020). It is necessary to assess how the perception of local inclusion rhetoric shifts with implementing entities that are pressured to uphold local inclusion norms, international implementing agencies, and those that are considered local enough but still indulgent of exclusionary practices, direct-access entities. Understanding implementing entities' identities, therefore, helps to uncover the underlying power dynamics operating within the climate finance regime, obscuring genuine local inclusion.

Chapter 2: Theory

2.1 Norm Diffusion and Theoretical Expectations

While IOs are traditionally seen as norm diffusers where they exert pressure on actors to adopt specific policies and practices, acting as socializing agents (Martins and Simmons, 2012; Finnemore & Sikkink, 1998), in the case of local inclusion in development, the UN and World Bank acted as norm consumers (Park, 2005). IOs can consume norms from non-state actors who seek to change the practices or behaviors of IOs. By condemning or applauding IO's initiatives, non-state actors can direct the actions of IOs, rather than IOs exploiting bureaucratic settings to maximize their preferences (Park, 2006). In response to polemic from non-state actors over stakeholder engagement, IOs, therefore, embraced the norm of local inclusion to improve their standing globally. Having consumed the local inclusion norm in development practices, the UN and its bodies, alongside the World Bank, now support the diffusion of an exploited local inclusion norm in the context of climate finance.

Bretton Woods institutions and the UN are often recognized as playing vital roles in the coordination to combat climate change (Gallagher et al., 2023). Socializing member states and non-state actors at G20 Summits, Annual COPs, or the Financing for Development conference (Jacobs, 2024), these prominent IOs have numerous opportunities to diffuse the local inclusion norm in mitigation and adaptation finance. The diffusion and commitment to this norm is further supported by the structure of MCFs, including the AF and GCF. These funds were born out of the UNFCCC framework, the Kyoto Protocol for the AF and COP16 for the GCF with both still remaining accountable to the UNFCCC in their decision-making (Chaudhry, 2020). The trustee of both funds is also the World Bank, responsible for the financial management of the AF and GCF. In the AF, the World Bank manages the sales of certified emissions reductions issued through the Clean Development Mechanism to fund the AF, along with increasing private and public donations (Adaptation Fund, 2019, Adaptation Fund, 2024b). The World Bank similarly oversees the assets and the receipts of the GCF, who receives financing from a range of public and private actors (Green Climate Fund, 2011). While the World Bank is expected to leave final decision-making to the MCFs, its expertise grants it authority in financial policy areas. Further, the UN and its agencies alongside the World Bank are also accredited as international implementing entities for the GCF and AF, as seen in Chapter 3 Figures 7 and 8. The GCF and AF are, therefore, susceptible to the influence of these prominent IOs.

While these funds exhibit organizational autonomy from member state and board influence, especially the Green Climate Fund (Gehring & Vizitu, 2024), the policy-guiding rules controlling member state preferences were born out of an IO environment. The AF and GCF cannot disentangle themselves from the structures of the UN and Bretton Woods institutions to serve as norm entrepreneurs themselves as they are held accountable to and depend on these international implementing entities for continued progress. This dependency allows IOs acting as international implementing entities to more easily diffuse norms in project implementation, particularly positive sentiment surrounding local inclusion rhetoric. Even if local inclusion is not implemented, or implemented poorly, international implementing entities will still frame this inclusion positively to meet the rhetorical commitments to local inclusion civil society and non-state actors previously called for. This expected behavior shows how international implementing entities exploit the local inclusion norm to support their own reputational standings over genuine local inclusion.

National and regional direct-access entities, on the other hand, tend to be considered more local in the climate finance regime (Browne, 2022: Colenbrander et. Al, 2018), even if this is not always the case, allowing them more flexibility in their perception of local inclusion rhetoric. While they may be inclined to advance their own agenda (Alcañiz & Giraudy, 2023; Price, 2021), the assumption of locality grants these entities presumed expertise allowing them to be more critical of local inclusion when challenges or obstacles arise. Limited institutional capacity of these implementing entities, along with the institutional innovations of MCFs discussed in the literature review, also restrict their abilities to effectively implement projects at the desired scale and timeline (Basak & Karlsson-Vinkhuyzen, 2022; Fenton et al., 2014), potentially deprioritizing local inclusion and impacting how this local inclusion is perceived during project execution. Based on these behavioral expectations garnered from norm diffusion theory, the following hypotheses are proposed:

H1: International entities are more likely to express a positive sentiment surrounding local inclusion rhetoric in project implementation than regional and national direct-access entities.

H0: International entities are not more likely to express a positive sentiment surrounding local inclusion rhetoric in project implementation compared to regional and national direct-access entities.

2.2 Model Specification

Based on these hypotheses, the independent variable is the type of implementing agency, either international, regional, direct-access regional or direct-access national, while the dependent variable is the average sentiment score surrounding local inclusion in MCF projects. Direct-access regional and direct-access national entities are distinguished due to the structure of the GCF and AF direct-access modality, explained further in the methodology section. The controls include the vulnerability and adaptation score per country, the civil society participation index per country, the fragile and conflict affected status of states, as well as the project budget (USD), the number of implemented projects per entity, project duration, the number of implemented projects per country, and the author of the project documents. These variables inform the following model:

Model specification:

$$\text{Sentiment Score} = \alpha + \beta_1 \text{Entity type}_{it} + \beta_2 \text{ Climate Adaptation}_{it} + \beta_3 \text{ Civil Society Participation}_{it} + \beta_3 \text{ Fragile State Index}_{it} + \beta_4 \text{ Project Budget}_{it} + \beta_5 \text{ Projects per Entity}_{it} + \beta_6 \text{ Project Duration}_{it} + \beta_7 \text{ Projects per Country}_{it} + \beta_8 \text{ Document Author}_{it}$$

i = completed project documents and annual project summaries from MCFs, t= (2010-2023)

Chapter 3: Methodology

3.1 Case Selection

To test H1, I will use the project documents of the GCF and AF, collected from the Climate Project Explorer dataset (Climate Project Explorer, 2025). The GCF and AF are the most suitable cases for this research question as they are the only MCFs that employ direct-access funding modalities. As of November 2024, 139 accredited entities were approved by the GCF, 52% of which were national (Green Climate Fund, 2024a). All implementing entities must seek accreditation to work with the GCF, paying an application fee based on the size of the entity, but direct-access entities must be nominated by a National Designated Authority, such as a government ministry. Applications are sent to the GCF Secretariat and Accreditation Panel for review, with their recommendations sent to the board for final approval (Green Climate Fund, 2025a). As of February 2025, the AF had 58 accredited implementing entities, 59% of which are national direct-access entities (Adaptation Fund, 2024a; Adaptation Fund, 2025a). All implementing entities working with the AF are accredited five years before seeking renewal, but national implementing entities must be nominated by designated authorities and approved by the accreditation panel before the board's final approval (Mathur-Filipp & Bista, 2015). These structural characteristics are compared below in Table 1.

Table 1: GCF and AF Comparison

Characteristic	**Green Climate Fund**	**Adaptation Fund**
Foundation	2010 at COP16 of the UNFCCC (Chaudury, 2020)	2010 under Kyoto Protocol of UNFCCC (Chaudury, 2020)
Year of Operationalization	2015 (Chaudury, 2020)	2010 (Chaudury, 2020)
Number of National Direct-Access Entities	72 as of November 2024 (Green Climate Fund, 2024a)	34 as of February 2025 (Adaptation Fund, 2025a)

The Global Environment Facility and Clean Investment Fund, which are also included in the Climate Project Explorer dataset, only use regional and international implementing agencies, rather than adopting direct-access modalities in their funding disbursement and are, therefore, disregarded (Global Environment Facility, 2025; Clean Investment Fund, 2025). The Climate Project Explorer dataset includes panel data, with different project documents, such as mid-term, approval, summary, and final evaluation reports, from the four largest MCFs from 1991 to 2024. The dataset, however, will be filtered to include one project document per project to understand how sentiment surrounding local inclusion is reflected throughout the project. For the AF, this document is either a final evaluation or project completion report whereas for the GCF, which has only officially completed two projects to date (Green Climate Fund, 2025b), this document will be the most recent annual project summary report. The dataset will also only include observations from 2010 to 2023, based on when the funds of interest became operationalizable (Climate Project Explorer, 2025), and the data available for the necessary controls. Due to these filtering steps, the dataset used will be a time-series. After the filtering steps are completed, there are 55 observations for the AF and 157 observations for the GCF. As both the GCF and AF use direct-access funding modalities and project documents are publicly accessible, these MCFs are the most feasible cases to use.

3.2 Empirical method and appropriateness

Using the project documents from the GCF and AF, I will perform a sentiment analysis followed by multiple OLS regressions in R to answer the research question. Sentiment analysis is used to analyze whether large volumes of text express negative, positive, or in some cases, neutral sentiment (Chan et al., 2021). R is the most appropriate tool to use for analysis due to its user-friendly and open-source access, along with the availability of necessary packages, such as the Lexicoder Sentiment dictionary. To perform sentiment analysis, a corpus of texts must be created. For this research, I will create one corpus with text extracted from the AF completed project documents and another corpus with the GCF documents to avoid systematic bias and ensure analysis remains internally valid. Before creating the document-feature matrix, I will use Key Words in Context (KWIC) to identify local inclusion rhetoric. This step is necessary because the research question is not interested in the sentiment of the document but rather the sentiment towards local inclusion as international implementing entities are expected to uphold a positive sentiment according to norm diffusion theory. The KWIC was created using the literature's existing interpretation of positive and negative words associated with local inclusion, seen in Table 2 below (United Nations Environment Program, 2022; United Nations Environment Program, 2023; Price, 2021).

Table 2: Local Inclusion Dictionary

KWIC: "local*", "equal*", "inclus*", "minorit*", "communit*", "access", "particip*", "civic", "indigenous", "subnational", "smallholders", "SMEs", "municipal", "cooperative", "decentralized", "village", "household", "town", "province", "rural", "country ownership", "flexib*", "accountab*", "gender", "race", "ethnic", "women", "traditional knowledge", "tradition*", "custom*", "exclu*", "marginaliz*", "discriminat*", "inequal*", "international", "hierarch*", "injust*", "rejec*"

The most frequent words that appear in the 30-word window before and between the KWIC are seen in Figures 1 and 2 below. Figure 1 shows the top features of the AF project documents with the "project" appearing most frequently at 32,634 times. "Women" also appears 7,843 times and is frequent in the GCF project documents with "women" appearing 50,344 times, "gender" appearing 43,417, and then "project" appearing the most at 60,790, as seen in Figure 2. The association of women and local inclusion from this preliminary review of project documents shows that gender inclusion may be used as a proxy for local inclusion.

Figure 1: Top Features of AF KWIC

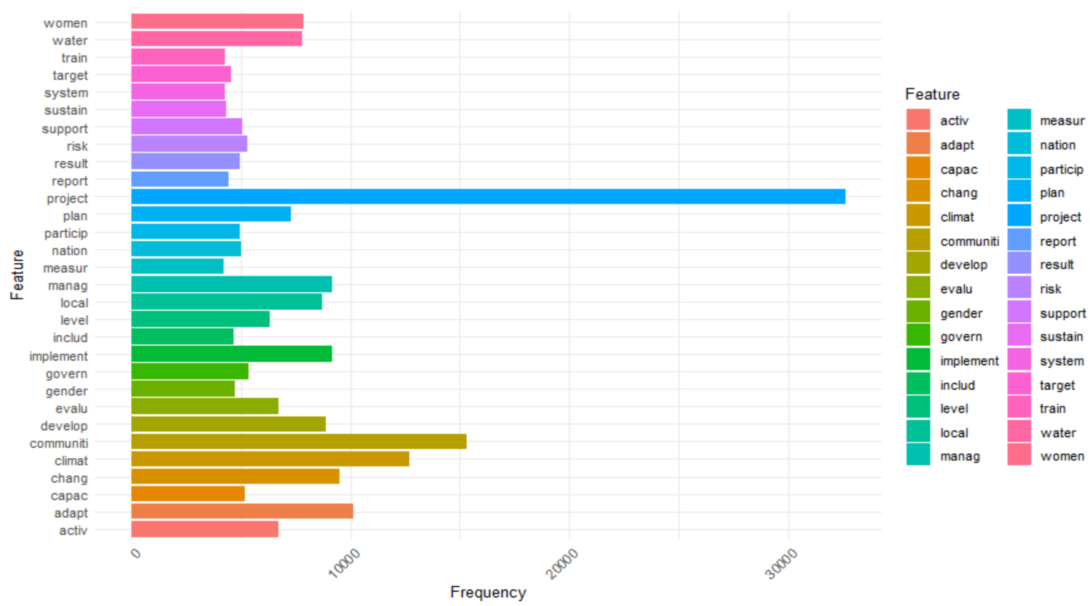
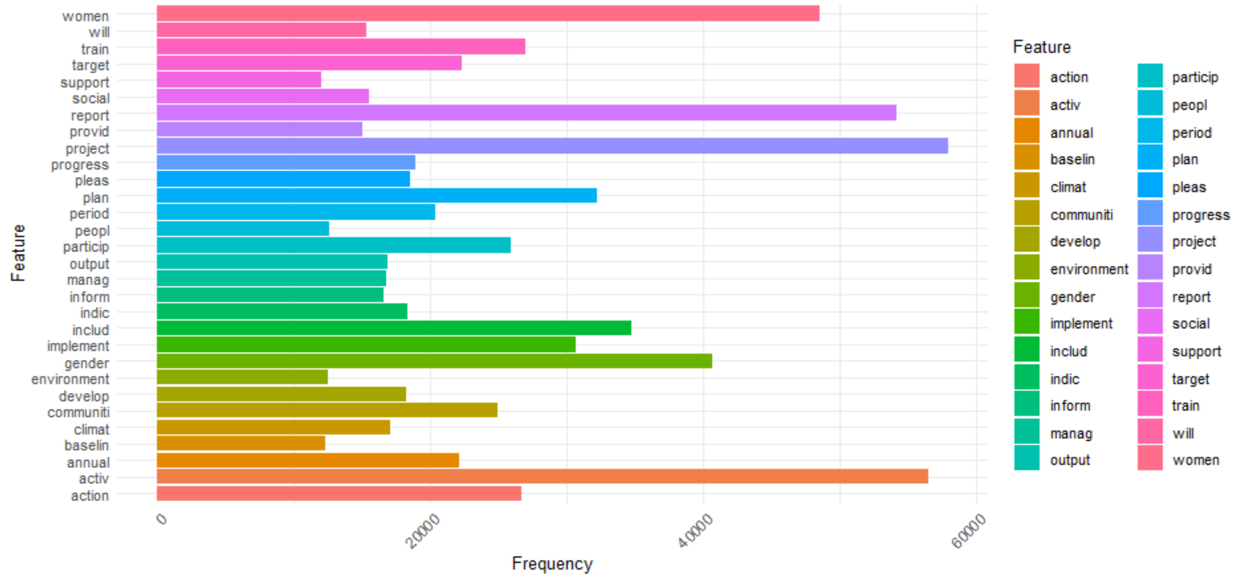


Figure 2: Top Features of GCF KWIC



Once the KWICs are acquired, these observations will be further pre-processed to create a document feature matrix that can be run through the Lexicoder sentiment dictionary (Young, & Soroka, 2012). Lexicoder was selected because it considers negation. Rather than classifying "not good" as one positive and one negative word, the dictionary considers this a negative word (Chan et al., 2021). A higher positive score indicates a more positive sentiment score while a negative score indicates negative sentiment. The sentiment scores calculated will be for the KWIC, therefore, I will create an average sentiment score for each project document based on the KWICs present in the documents. I will also normalize this score, dividing it by the number of pages per document as project documents can range anywhere from two to 209 pages for the AF and three to 145 for the GCF. While semi-supervised machine learning could also be used to analyze sentiment, a KWIC-based sentiment analysis is more appropriate to examine the theoretical expectations of how the type of implementing agency influences sentiment surrounding local inclusion rhetoric, especially given the time constraints and data availability of this thesis.

3.3 Variables

Once I have completed the sentiment analysis, I can use the average sentiment score for each AF and GCF project document along with the applicable independent variables to execute the multiple OLS regressions. The independent variables, used as controls, include the project budget, project duration, and the document author, and are all extracted from the Climate Project Explorer dataset. I will merge this dataset with the AF project dataset, and the GCF Entities

Dataset, both publicly accessible (Green Climate Fund, 2024c; Adaptation Fund, 2024d). These datasets include additional information, such as the number of projects implemented per entity and the number of projects implemented per country, which can clarify how large-scale projects impact sentiment surrounding local inclusion. These datasets also include the type of entity involved, which is the principal independent variable of interest. The operationalization of the independent and dependent variables, as well as controls, are summarized in the table below:

Table 3: Variables

Variable Type	**Name**	**Measurement**	**Source**
Independent Variable (Categorical)	Implementing Agency Type	1= national direct-access entity 2= regional direct-access entity 3= regional entity 4 = international entity	(Green Climate Fund, 2024c; Adaptation Fund, 2024d)
Dependent Variable (Quantitative Continuous)	Sentiment Score	Sentiment score per project document (normalized by number of pages per document)	(Climate Projects Explorer Dataset, 2025)
Control (Quantitative Continuous)	Climate Adaptation	Score from 0 to 100, with 100 being the best, measuring a country's ability to leverage investments into climate adaptation projects and vulnerability to climate change	(Notre Dame Global Adaptation Initiative Country Index, 2024)
Control (Quantitative Continuous)	Civil Society Participation	Score from 0 to 1, with 1 being the best, based on citizens' ability to influence policymakers	(Herre et al., 2023)
Control (Quantitative Continuous)	Fragile State Index	Score from 0-120, with 120 being the most fragile based on social, political, economic, security, and marginalization indicators	(Fund for Peace, 2023)

Control (Quantitative Continuous)	Project Budget	Project budget in USD per project	(Climate Projects Explorer Dataset, 2025)
Control (Quantitative Discrete)	Projects per entity	The total number of projects an entity has implemented	(Climate Projects Explorer Dataset, 2025)
Control (Quantitative Discrete)	Project Duration	Length of project in years	(Climate Projects Explorer Dataset, 2025)
Control (Quantitative Discrete)	Projects per Country	Total number of projects completed or ongoing in a country	(Climate Projects Explorer Dataset, 2025)
Control (Categorical)	Author of Project Document	1= Internal (written by the multilateral fund or participating project entity) 2=External (written by an entity external to the fund i.e. independent evaluator or consultant)	(Climate Projects Explorer Dataset, 2025)

The independent variable distinguishes the type of direct-access entity, between regional and national, as the GCF includes regional and national direct-access entities, while the AF only includes national direct-access entities. Project duration, project budget, and projects per entity are also all important when measuring the institutional capacity of implementing entities (Basak & Karlsson-Vinkhuyzen, 2022; Fenton et al., 2014), and its impact on sentiment score. International implementing entities with more experience and capacity, as measured by these controls, are more likely to exert sufficient influence in diffusing the reinterpreted local inclusion norm, where sentiment surrounding local inclusion rhetoric is more positive even if local inclusion is unsuccessful on the ground. In Figure 3, based on the filtering requirements for projects, international implementing entities account for four (21%) of the 19 entities that have completed projects, yet Figure 4 shows they distribute 77% of funding allocated by the AF. Similarly, international implementing entities account for 22 (50%) of the GCF's 44 implementing entities working on active or completed projects yet disburse 82% of funding. The relationship between international implementing entities and financial capacity emphasizes the assumed trust between MCFs and their international implementing entities, making MCFs more malleable to norm diffusion.

Figure 3: Type of Implementing Entities for the AF and GCF based on Filtered Projects

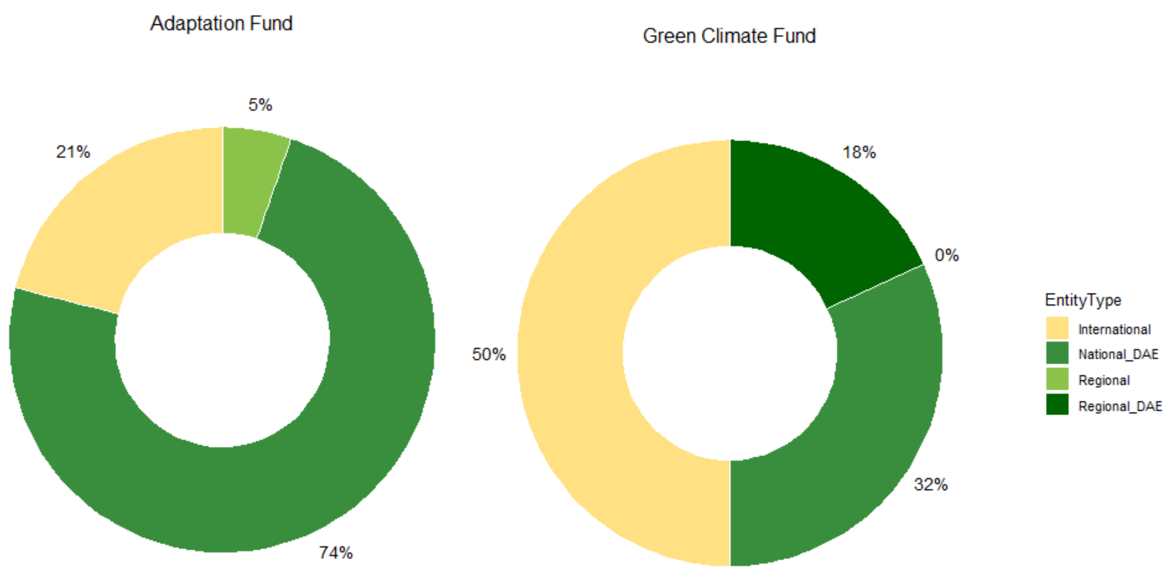
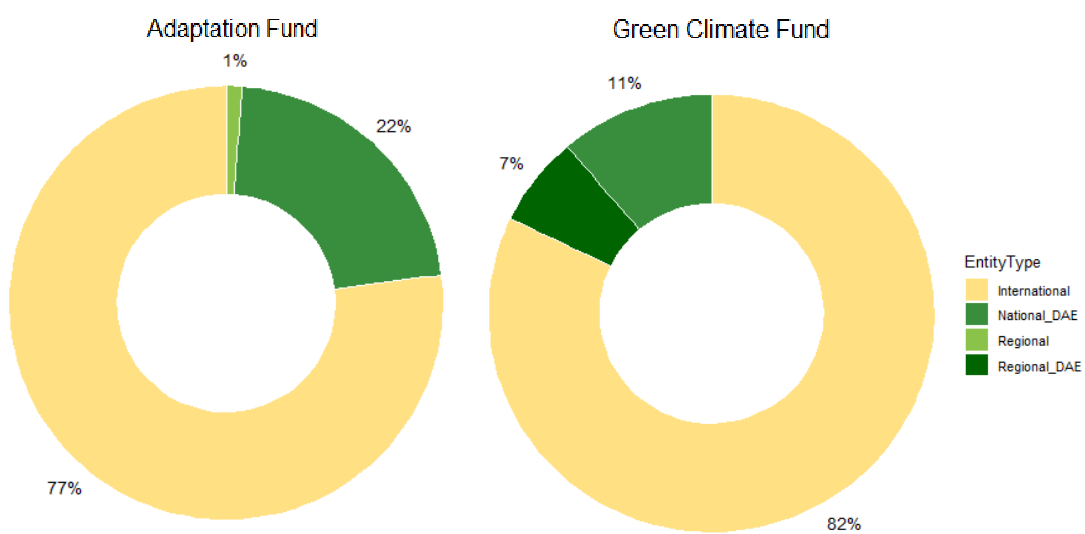


Figure 4: Total Funding Disbursed by Entity for the AF and GCF



International implementing entities tend to execute longer projects in the AF, whereas in the GCF, implementing entity type appears not to affect project duration, as seen in Figures 5 and 6. As a proxy for institutional capacity, international implementing entities executing longer projects in the AF may be operating at a larger scale to reach beneficiaries and achieve project outcomes. Large-scale operations demonstrate the authority of international implementing entities in their knowledge of project execution, and in turn, their ability to influence sentiment surrounding local inclusion rhetoric.

Figure 5: AF Average Completed Project Duration by Entity Type

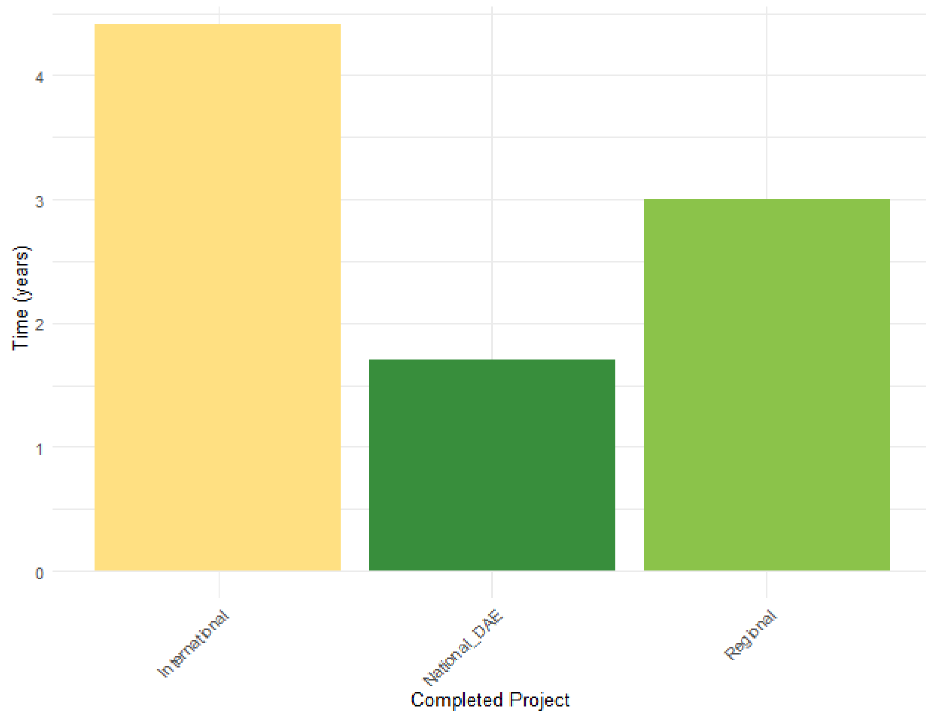
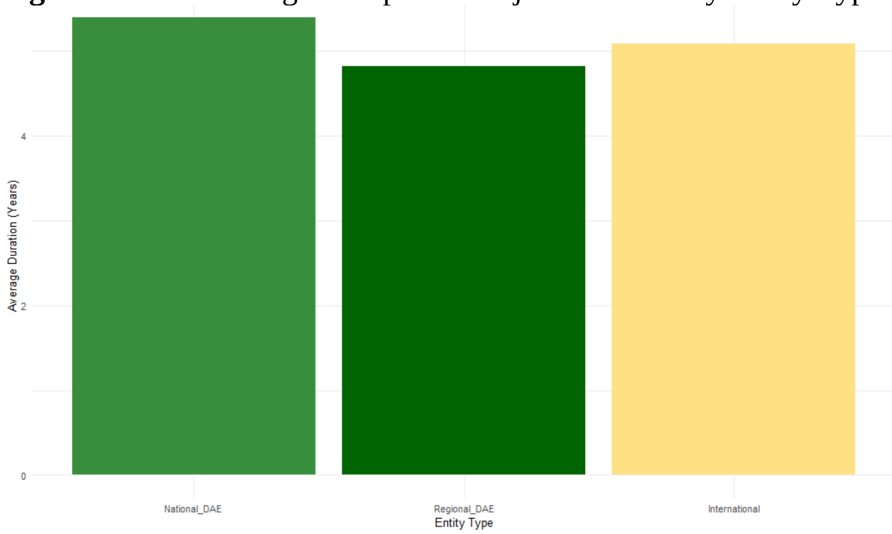


Figure 6: GCF Average Completed Project Duration by Entity Type



The implementing entity that receives and distributes the most funding for the AF is the United Nations Development Program (UNDP) at a total of 135.3 million USD, as seen in Figure

7. The International Bank for Reconstruction and Development Association, or World Bank, distributes the most funding for the GCF, a total of 1.1 billion USD, as seen in Figure 8. Both international implementing entities are seen as the traditional players in norm diffusion theory (Park, 2005; Park, 2006), illustrating their ability to influence sentiment surrounding local inclusion in project documents.

Figure 7: AF Total Funding Disbursed for Completed Projects by Implementing Entity

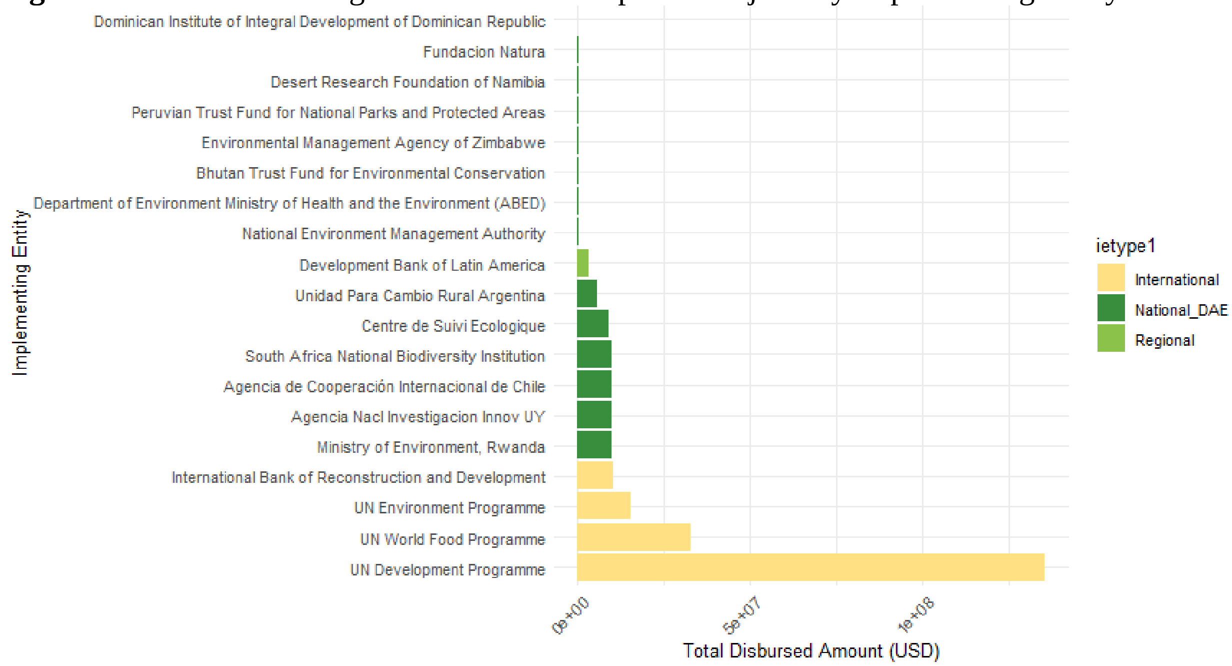
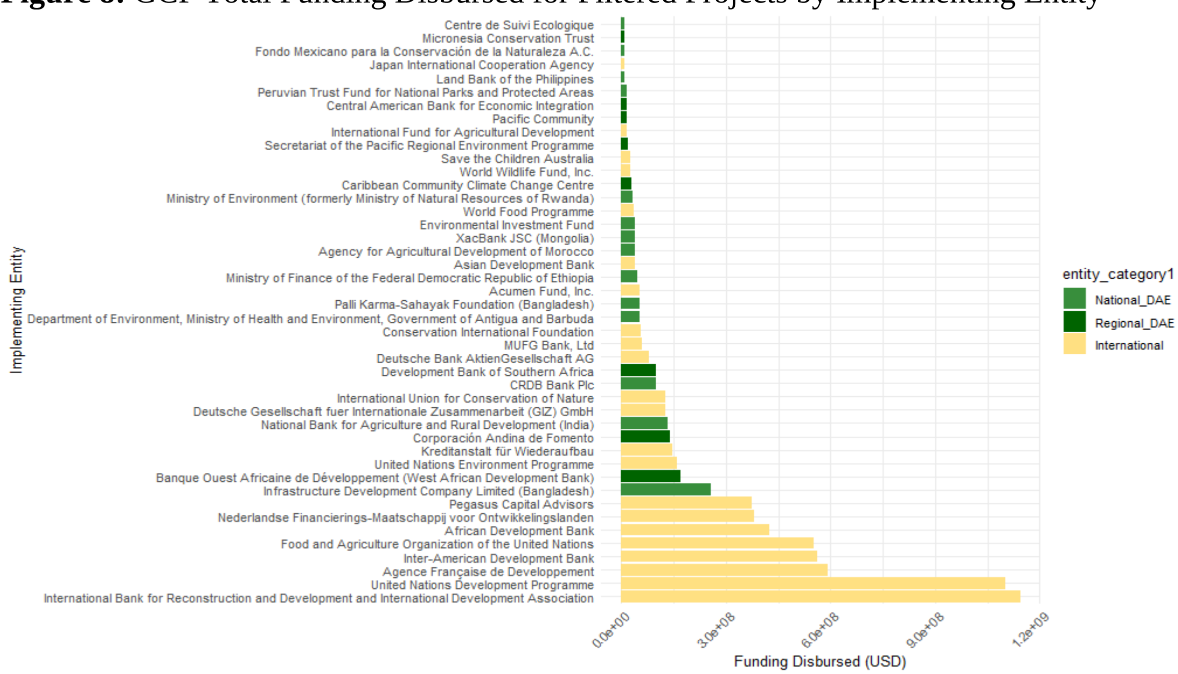


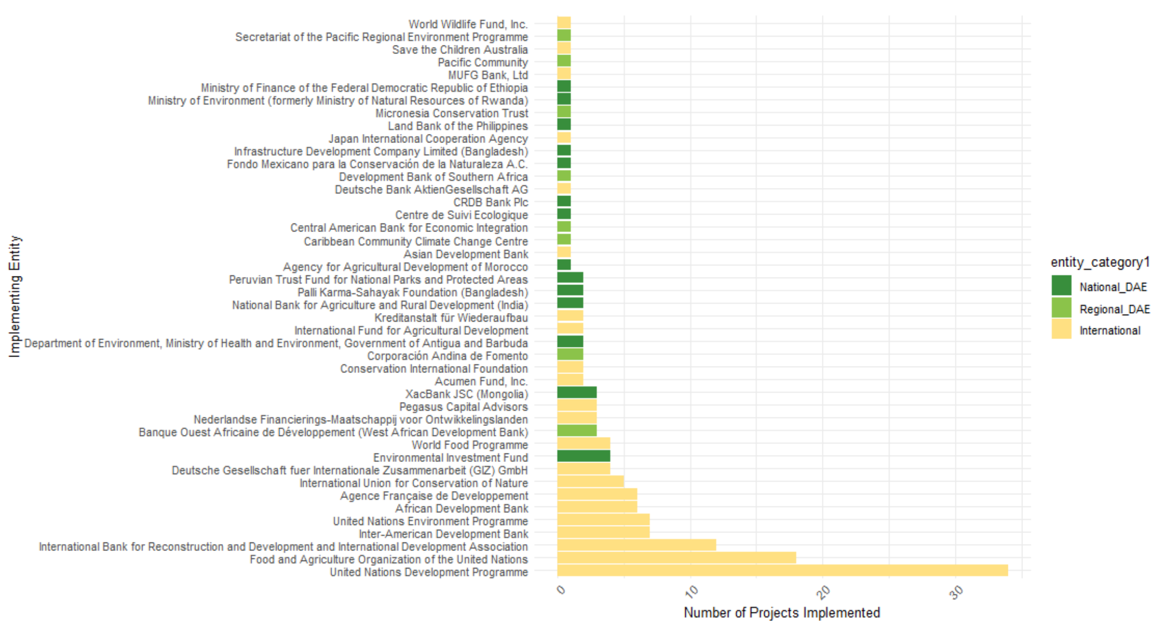
Figure 8: GCF Total Funding Disbursed for Filtered Projects by Implementing Entity



The UNDP is the largest implementer of projects for both funds, executing 34 projects for the GCF and 21 for the AF, as seen in Figures 9 and 10, where international entities tend to implement more projects, due to their established credibility. These proxies for institutional capacity of entities (project duration, project budget, projects per entity) are necessary to understand and control as they help determine the power of implementing entities (Basak & Karlsson-Vinkhuyzen, 2022; Fenton et al., 2014; Basak & van der Werf, 2019), and as a result, their ability to dictate sentiment surrounding local inclusion.

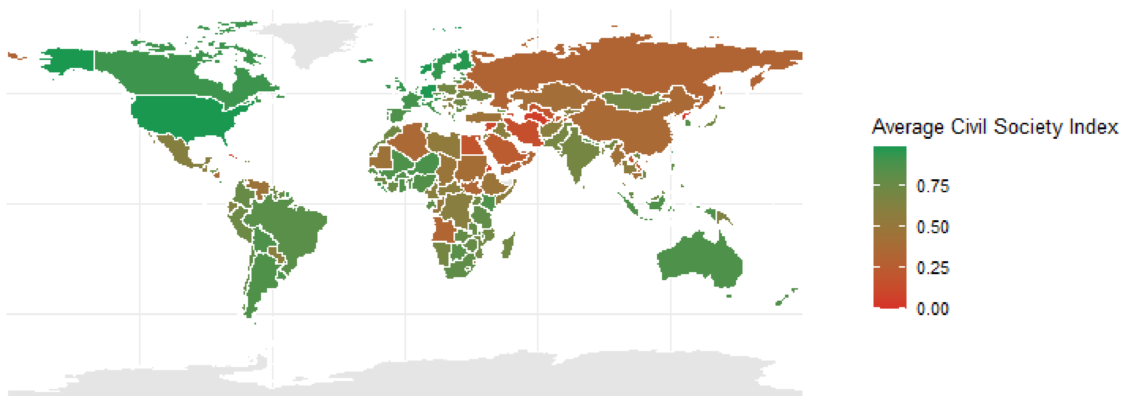
Figure 9: AF Completed Projects per Entity

Figure 10: GCF Projects Implemented per Entity



Using multiple measurements of controls for country governance, stability, and institutional capacity (projects per country, average climate adaptation score, average civil society index, and average fragile state index) also improves the internal validity of the study. Controlling institutional capacity, governance, and stability of states is necessary as countries with more democratic norms are expected to condone criticism of MCF and implementing entities' practices (Diamond, 2024), potentially influencing sentiment towards local inclusion. Figure 11, for example, shows the MENA region, Russia, and China as all having civil society scores lower 0.500, indicating a suppression of democratic rights and unstable governance (Herre et al., 2023), and potentially impacting the ability to express sentiment surrounding local inclusion rhetoric.

Figure 11: Average Civil Society Index (2010-2023)



The average climate adaptation score, in Figure 10, shows that countries in Sub-Saharan Africa have scores lower than 40 as these countries have a high vulnerability to climate change as well as a limited capacity to receive and implement climate finance (Notre Dame Global Adaptation Initiative Country Index, 2024). Controlling for institutional capacity, via the ability to implement adaptation financing, vulnerability to climate change with the average climate adaptation score also ensures that varying country needs and capacities do not impact sentiment score surrounding local inclusion rhetoric. Countries more vulnerable to climate change with less capacity to implement climate financing, for example, may produce negative sentiment surrounding local inclusion rhetoric under the assumption that projects are not sufficiently meeting adaptation goals or successfully working with local entities.

Figure 13 also shows the average fragile state index, with countries in Sub-Saharan Africa likely to have a score closer to 90, with other regions such as the MENA region including scores of 80 or above, indicating poor governance and institutional structures (Fund for Peace, 2023).

Controlling state fragility is also necessary to address country bias where projects tend to be implemented in more stable countries (Doshi & Garschagen, 2020; Saunders, 2019), impacting the implementing entities' ability to work with local organizations, and in turn, sentiment towards local inclusion rhetoric.

Figure 12: Average Climate Adaptation Score (2010-2023)

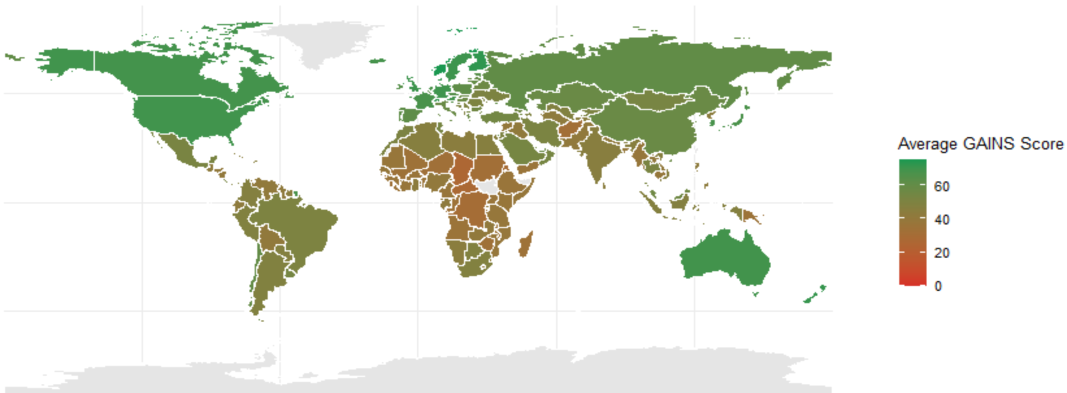
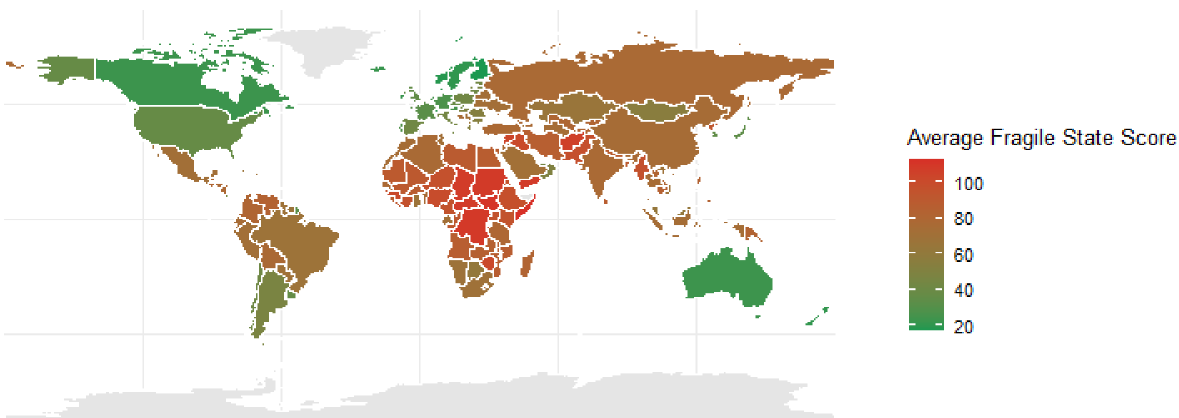
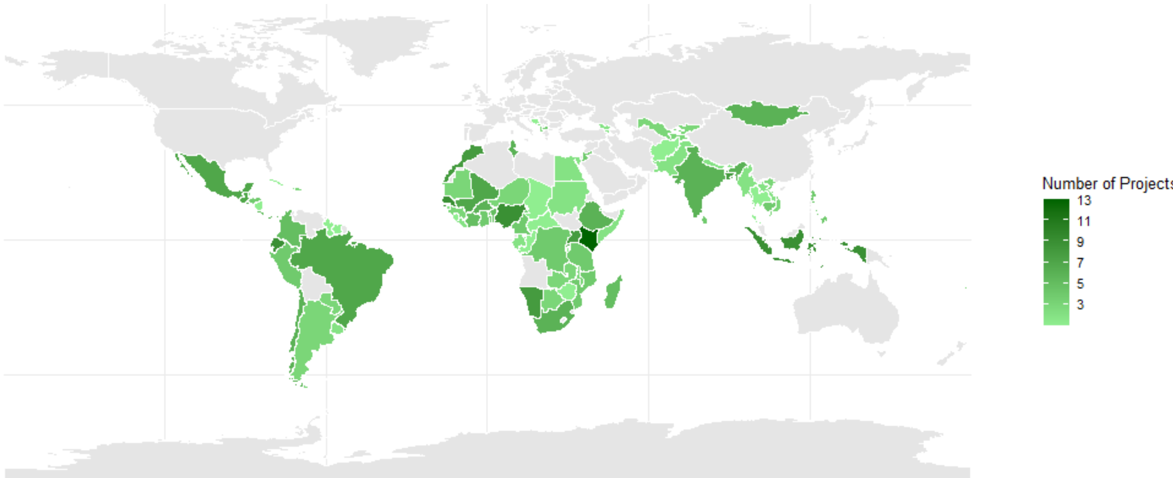


Figure 13: Average Fragile State Index (2010-2023)



In addition to these three measurements of institutional capacity and democracy of countries, projects per country also reflect MCFs' preferences to work in countries at risk of climate change with governments that display sufficient capacity to implement mitigation and adaptation projects, potentially impacting sentiment score. For example, 13 individual and multi-country GCF projects are ongoing in Kenya, as seen in Figure 14, most likely due to its relatively stable civil society score of 0.870, despite its fragile state score of 95.342. Its lower climate adaptation score of 38.508, however, indicates a vulnerability to climate change but enough structural and institutional capacity to implement climate finance projects, potentially impacting sentiment score surrounding local inclusion rhetoric positively.

Figure 14: GCF Projects per Country



The country with the most completed projects for the AF is South Africa, with three completed projects as seen in Figure 15. South Africa also shares similar qualities with Kenya in terms of country governance and stability controls, offering the same rationale for project location. South Africa exhibits a stable civil society score of 0.809, with a higher fragile state index of 69.557. Similarly, its lower climate adaptation score of 48.649, shows a vulnerability to climate change but sufficient structural and institutional capacity to implement mitigation and adaptation projects, demonstrating how country dynamics can impact the extent of inclusion and impact on sentiment score surrounding local inclusion rhetoric in project implementation.

These country controls provide insights into the institutional capacities of recipient countries, whose stability reflects varying abilities to support or hamper project implementation (Doshi & Garschagen, 2020; Ciplet et al., 2022; Saunders, 2019), and as a result, sentiment surrounding local inclusion. These variables are also all summarized in the statistics table below. Sentiment per page in the AF is reduced from 55 to 53 as two documents contained no local inclusion rhetoric to analyze. Due to data availability and the appropriateness of the methodology, sentiment analysis and multiple OLS regressions are the most feasible methodologies to answer the posed research question.

Figure 15: AF Completed Projects Per Country

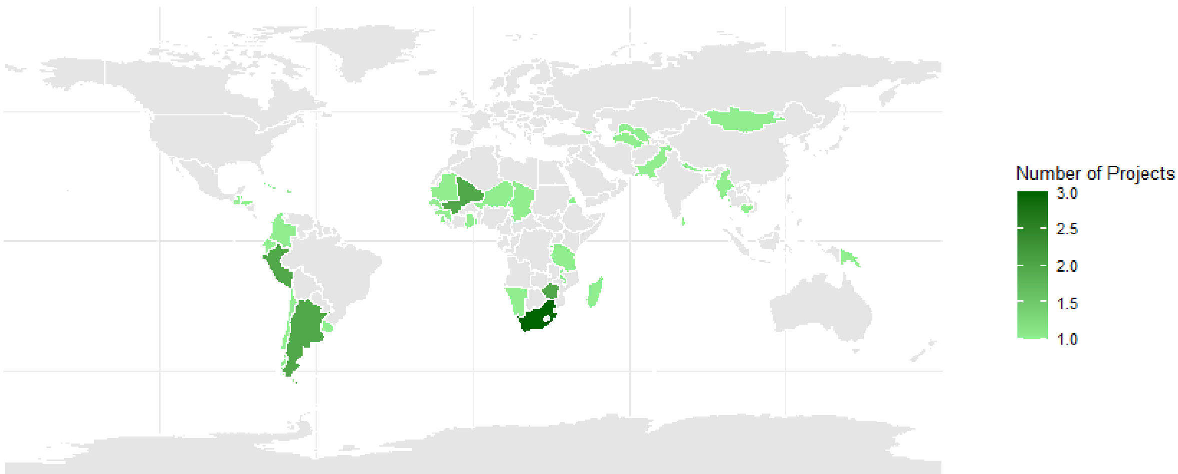


Table 4: Summary Statistics Table

Variable	Mean	Std..Dev.	Min.	Max.	N
Dependent Variables					
sentiment_per_pageAF	5.777	4.309	-1.667	15.708	53
sentiment_per_pageGCF	7.401	4.452	-2.600	25.768	157
Independent Variables					
amount_disbursedAF	4565913.236	3506542.012	0	9969619	55
Financing_disbursedGCF	47312090.074	53504265.921	2320388	280000000	157
author_typeAF	0.655	0.480	1	2	55
author_typeGCF	1.013	0.113	1	2	157
projects_per_entityAF	9.945	8.941	1	21	55
Project_per_EntityGCF	12.478	12.418	1	34	157
projects_per_countryAF	1.291	0.567	1	3	55
Project_per_countryGCF	2.019	1.232	1	6	157
implementing_entity_typeAF	2.109	0.994	1	3	55
implementing_entity_typeGCF	3.420	1.127	1	4	157
avg_civil_score	0.596	0.299	0	0.985	199
avg_fsi_score	69.101	23.472	17.686	112.871	179
avg_climate_adaptation_score	47.692	13.251	0	75.339	192

Initial correlation also shows the relationship between sentiment score and implementation entity type. In Figure 16, the boxplots show a correlation between entity type and sentiment score, with the AF project documents. For entity type 1 (national direct-access), the median sentiment is 1.917, with sentiment ranging from 9.600 to -1.667. Entity type 3 (regional) shows a median and mean sentiment of 10.359 and is only marked by a single line as there is only one observation for entity type 3 in the AF corpus, as confirmed in Table 5. Entity type 2 is not present as the AF does use regional direct-access entities. This is only a modality seen in the GCF. Entity type 4 (international) has a median sentiment of 7.112, ranging from 15.708 to 1.670. The mean sentiment of national direct-access entities is 3.409 whereas the mean sentiment of international entities is 7.361, as seen in Table 5.

Figure 16: Box Plot for Sentiment Score by AF's Implementing Entity

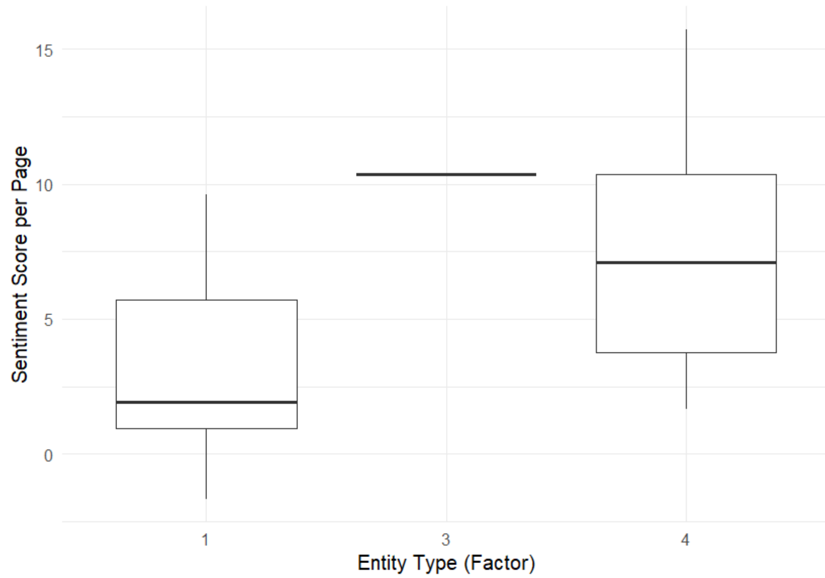


Table 5: Sentiment Score in Relation to Entity for AF

ietype_factorAF	mean_sentiment	median_sentiment	count
1	3.409	1.917	24
3	10.359	10.359	1
4	7.361	7.112	30

Looking at the correlation between implementing entity type and sentiment score with GCF project documents, the boxplot in Figure 17 shows that there is no relationship between entity type and sentiment score, foreshadowing the multiple OLS regression results. Entity type 1 (national direct-access) has a median of 7.403 sentiment score, ranging from 10.788 to 2.046. Entity type 2 (regional direct-access) shows a similar median of 7.038, ranging from 11.849 to 2.840. Entity type 4 (international) also has a similar median of 7.174, ranging from 25.768 to -2.600. The average mean sentiment per entity category only slightly ranges from 6.865 to 7.520, perhaps explained by the limited number of observations for regional direct-access entities compared to international implementing entities and national direct-access entities, as seen in Table 6.

Figure 17: Box Plot for Sentiment Score by GCF's Implementing Entity

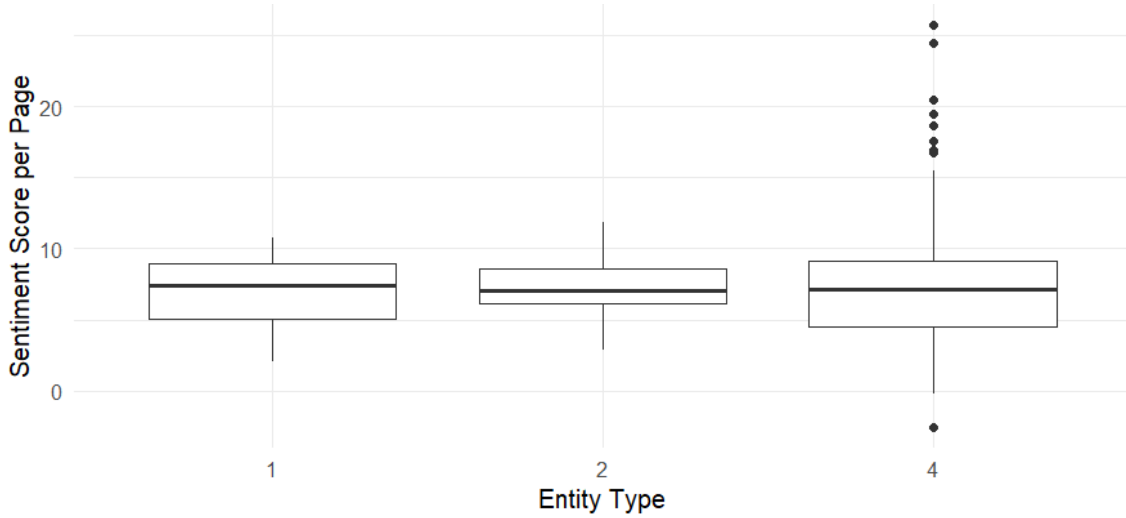


Table 6: Sentiment Score in Relation to GCF Entity Type

entity_categoryfactorGCF	mean_sentiment	median_sentiment	count
1	6.865	7.403	23
2	7.194	7.038	11
4	7.520	7.174	123

Based on the results of the multiple OLS regression results, I will perform a brief, most similar case comparison to further understand the causal mechanisms linking the statistically significant variables to sentiment score per page surrounding local inclusion rhetoric. A most similar case comparison is based on John Stuart Mill's Method of Difference, in which two cases are nearly identical regarding all independent variables except for one and result in different outcomes. This method allows the researcher to isolate variables and uncover potential causal mechanisms to help explain the differing effects on the dependent variable. The most similar case comparison, however, does not account for equifinality, where multiple variables or a combination of variables may cause different outcomes among the selected cases (Bennet, 2004). Despite the stringent conditions it requires, a most similar case study in tandem with multiple OLS regressions can uncover relevant causal mechanisms to help explain the rejection or acceptance of H1 or H0. This case comparison can be used to compare projects within the AF or GCF to understand the impact of different implementing entities on sentiment score. It can also be used to compare similar implementing entities, such as two international implementing entities, operating in different if the AF and GCF to see how the structure of MCFs impacts sentiment score. The following chapter explores the results of the multiple OLS regressions performed for the AF and GCF.

Chapter 4: Analysis

4.1 Multiple OLS Regression Results

Table 7 below shows the results of the multiple OLS regression for Model 1, using the AF project documents and related information, and Model 2, using the GCF project documents and related information. When running an OLS regression in R, categorical variables are converted to numeric variables using the dummy variable format. As the research question is interested in the impact of different types of implementing entities on the sentiment surrounding local inclusion rhetoric, a reference level needs to be created before running the multiple OLS regressions. This separates the implementing entity type variable coded as 1,2,3,4, as defined in Table 3, into distinct categories, where the national direct-access entity is set as the reference level, shown by the additional label of (Constant) in Table 5. The coefficient calculated for the constant is interpreted as the expected sentiment score for national direct-access when all other independent variables in Models 1 and 2 are held constant. The coefficient calculated for the international implementing entity variable is the difference in expected sentiment score between national direct-access and international implementing entities. The coefficient calculated for the regional entity variable is the difference in expected sentiment scores between regional entities and national direct-access entities and so on. Selecting the reference level for the implementing entity type variable in the multiple OLS regression does not affect the overall fit or differences between the categories; yet, changing the reference level would recalculate the coefficients in the model. These names differ from Table 4 of Chapter 3, where implementing type is denoted by implementing_entity_typeAF and implementing_entity_typeGCF because the dummy variable separates the implementing entity type variable denoted by 1,2,3,4 into distinct categories. The data used also differs according to the model, as Model 1 use the entity type data from the AF dataset, whereas the entity type variables in Model 2 use the entity type data from the GCF dataset.

Based on the results of Model 1, the international implementing entity variable is significant at the 1% level (p-value < 0.01), meaning when all variables are held constant, the difference in sentiment score between national direct-access and international implementing entities is 7.148, a positive sentiment score. When all variables are 0, the difference in sentiment score between direct-access entities and regional entities is 5.279, however, this relationship cannot be confirmed as there is only one observation for regional entities in the AF. Therefore, H1 is partially accepted as international implementing entities are more likely to express positive sentiment surrounding local inclusion rhetoric in the AF than national direct-access entities, but not necessarily regional entities. H0 can also only be partially rejected until further observations can confirm the relationship between regional entity type and sentiment score. The adjusted R^2 value of Model 1 is also 0.274, showing moderate explanatory power of the differences between implementing entity type on the impact of sentiment score. The projects per entity variable is also significant at the 5% level ($p\text{-value} < 0.05$), meaning that when all variables are held constant, sentiment score decreases by -0.220 with every increase of an additional project per entity. The regional direct-access entity variable is absent as the AF only offers the direct-access modality to national implementing entities. Some controls also do not have country-specific values, such as the civil society index failing to include small Pacific Island states. Two observations are also removed as no local inclusion rhetoric was detected in the documents. This drops the number of observations included in the regression from 55 to 49.

The results of Model 1 are visualized in Figure 18 below. This figure shows the estimated coefficients when all other variables are held constant and their confidence intervals, indicated by the line. The intercept associated with the national direct-access variable has the largest standard of error (10.29) accounting for its larger confidence interval. As the national direct-access entity variable was set as the reference level, this coefficient is the expected sentiment score when all other predictors are held constant. Yet, this estimate may be less precise if 0 is not a plausible value for all independent variables, accounting for the large confidence interval. For example, FSI score does not include a score of 0 for countries, as seen in the summary statistics table in Chapter 3, meaning there is higher unpredictability surrounding the intercept term representing the estimate of the national direct-access entity variable when all other variables are held constant at 0, but not necessarily a higher uncertainty about the relative effect of national direct-access entities to other variables. While an OLS regression is often visualized with a point-slope plot, the independent variable of interest (implementing entity type) is a categorical not continuous variable, making it difficult to visualize linearly. Figure 18 also helps visualize the effects of each variable on sentiment score not just implementing entity type, where variables are likely to be statistically significant if their confidence interval does not cross 0.

In Model 2, on the other hand, H1 fails to be accepted as does H0. This model, using GCF project documents and GCF specific independent variables, also uses the reference methodology to split implementing entity types. Similarly, due to the country limitations of the controls, the number of observations included in the regression drops from 157 to 142. No value is present for the regional entity variable as no projects analyzed were implemented by regional entities, only regional direct-access entities. Each implementing entity type does not significantly impact the sentiment score of local inclusion rhetoric in a statistically significant manner. Instead, the project duration variable is significant at the 5% level (p-value < 0.05), meaning that when all variables are held constant, for every increase in one year of a project's duration, sentiment score will decrease by -0.546. As was the case in Model 1, in Model 2, the projects per entity variable is also significant, referring to the number of projects each entity has implemented. This variable is significant at the 1% level (p-value < 0.01), meaning for every additional project an entity works on, the sentiment score will increase by 0.131. Figure 19 visualizes Model 2 using the estimates of coefficients and similarly shows a large confidence interval for direct-access entities, with the coefficient of all other variables, including those that are statistically significant, estimated as well. The adjusted R^2 value for Model 2 is also 0.096 indicating a weaker explanatory power, meaning the relationship between the difference in implementing entity type on sentiment score is weaker, however, the robustness checks performed below indicate the model is still statistically reliable.

Table 7: AF and GCF Multiple OLS Regression Table

	AF Sentiment per Page (Model 1)	GCF Sentiment per Page (Model 2)
Regional Entity	5.729	
	(4.160)	
International Entity	7.148***	-0.357
	(2.284)	(1.270)
Regional Direct-Access		-0.312
		(1.931)
avg_climate_adaptation_score	0.037	-0.075
	(0.141)	(0.103)
avg_civil_score	-0.181	0.312
	(3.064)	(2.377)
duration	-0.703	-0.546**
	(0.926)	(0.221)
avg_fsi_score	-0.016	-0.065
	(0.060)	(0.049)
amount_disbursed (USD)	0.00000	-0.000
	(0.00000)	(0.000)
author_type	1.431	0.615
	(3.305)	(4.476)
projects_per_country	1.319	0.267
	(1.020)	(0.325)
projects_per_entity	-0.220**	0.131***
	(0.096)	(0.034)
National_direct_access (Constant)	1.249	16.395
	(10.296)	(10.281)
N	49	142
R^2	0.425	0.160
Adjusted R^2	0.274	0.096
Residual Std. Error	3.679 (df = 38)	4.342 (df = 131)
F Statistic	2.809** (df = 10; 38)	2.491*** (df = 10; 131)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Figure 18: Coefficient Estimates of Model 1

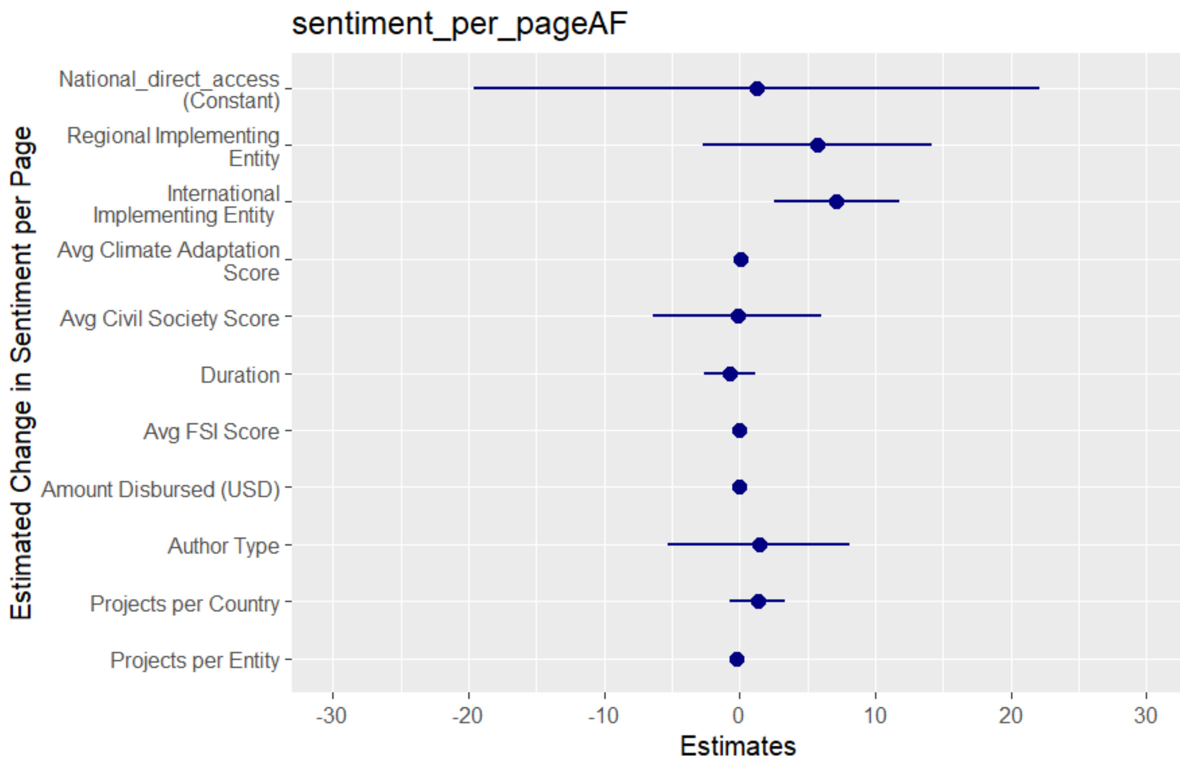
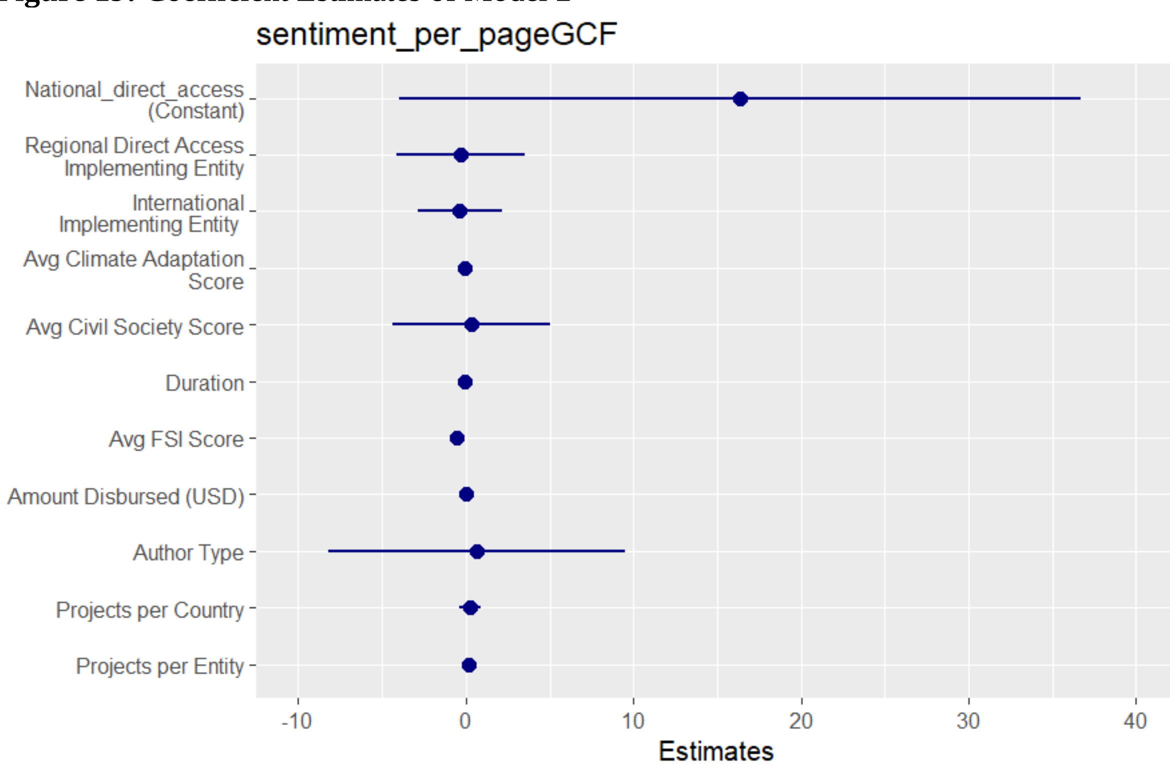


Figure 19: Coefficient Estimates of Model 2



4.2 Robustness Checks

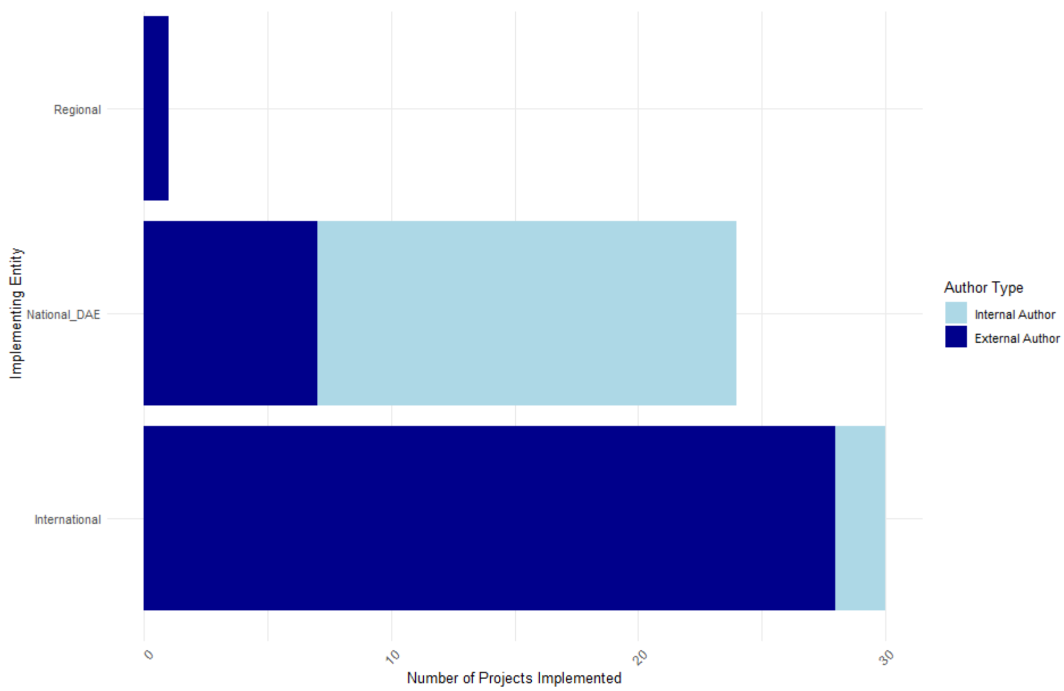
Robustness checks further confirm the relationship established in Model 1 between sentiment score and implementing entity type and the lack thereof in Model 2. To improve the internal validity of the multiple OLS regressions, I test for multicollinearity in Models 1 and 2 to understand the level of correlation between independent variables and their impact on the estimated coefficients (Dougherty, 2011). Table 8 shows the multicollinearity of variables in Model 1 based on the Variance Inflation Factor (VIF) test performed in R.

Table 8: Multicollinearity Scores for AF

Variable	GVIF	Df	$GVIF^{(1/(2*df))}$
ietype_factorAF	5.683	2	1.544
avg_climate_adaptation_score	3.035	1	1.742
avg_civil_score	1.518	1	1.232
duration_AF	10.946	1	3.308
avg_fsi_score	3.255	1	1.804
amount_disbursedAF	3.516	1	1.875
author_numericAF	8.697	1	2.949
projects_per_countryAF	1.289	1	1.135
projects_per_entityAF	2.668	1	1.633

Using the car package with the vif function, this test is one of the most effective and standard tests to measure the presence of multicollinearity in a multiple OLS regression. The Generalized Variance Inflation Factor (GVIF) is the same as VIF, but accounts for categorical variables, which in this Model is the implementing entity type. GVIF seeks to measure the degree of sampling variance among the coefficients and how this correlation impacts the regressors. Uncorrelated regressors result in an R^2 of 0 or a VIF of 1. The traditional thresholds when analyzing VIFs are 5 for moderate multicollinearity and 10 for high multicollinearity. The scaled GVIF ($GVIF^{(1/(2*df))}$) is the square root of the GVIF and takes into account multiple terms by including the DF, degrees of freedom in the calculation, to ensure the scaled GVIF is comparable to GVIF values with one DF (Fox & Monette, 1992). The DF is two for ietype_factorAF as it is split with the set reference level. With the multilevel variables, it is, therefore, more appropriate to analyze the Scaled GVIF factor. In this case, ietype_factorAF is 1.54, which is below both thresholds for multicollinearity. The remaining variables have one degree of freedom and show two variables above certain thresholds. Table 8 indicates that duration_AF's GVIF is 10.946, which is above the 10 threshold for high multicollinearity. Author numeric's GVIF is 8.697, which is above the 5 threshold for moderate multicollinearity. The high multicollinearity for the duration variable may be a result of international implementing entities having on average longer projects in the AF, as seen in Chapter 3 Figure 5. The author numeric type also seems to correlate with international implementing entity type, where external authors are most likely to evaluate internationally implemented projects, as seen in Figure 20. High multicollinearity makes it difficult for Model 1 to isolate the individual effect of each independent variable on the sentiment score, meaning it can change the weight of the coefficients, inflate standard errors, or make it difficult to interpret individual effects because the highly multicollinear variables are more intertwined. While removing duration and author numeric could improve the statistical reliability of the remaining coefficients, it may lead to omitted variable bias where an important predictor of sentiment score is removed leading to bias in other variables.

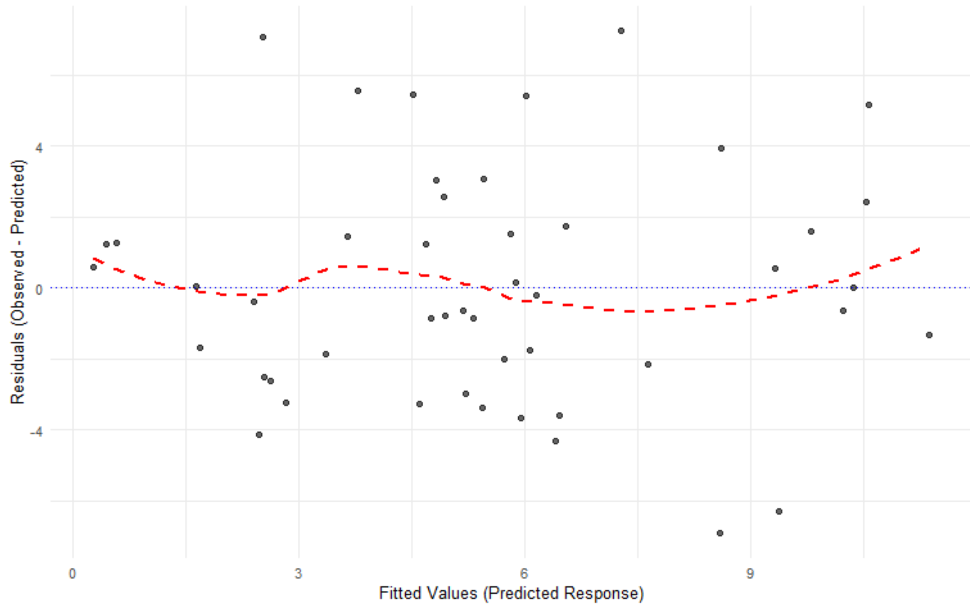
Figure 20: Author Type and Implementing Entity Type AF



Heteroskedasticity is also tested, which assesses if the variance of errors is related to the independent variables used in the model (Dougherty, 2011). Performing heteroskedasticity is important to understand whether the standard of errors are incorrect and, as a result, contribute to incorrect p-values. This test can be performed using the Breusch-Pagan test. Considered a more robust measure of heteroskedasticity, this test in R looks at whether variance is related to independent variables by using a chi-squared test to see how the test statistics are distributed. In

R, this test is performed with the lmtest package and the bptest function. When the test statistic has a p-value below the selected p-value threshold, heteroskedasticity is present (Breucsh & Pagan, 1979). The BP test for Model 1 results in a p-value of 0.221. This p-value is greater than the chosen significance level of 0.10 used in Model 1, meaning heteroskedasticity is not present. The absence of heteroskedasticity is confirmed in Figure 21, where the trend of residuals across the range of fitted values is summarized in the red dotted line, which remains consistently close to 0 and shows limited fanning out. Therefore, the residuals of Model 1 are not inflated, and the statistical significance of the variables found in Model 1 can be confirmed.

Figure 21: Residuals vs. Predicted Values in Multiple OLS Regression of Model 1



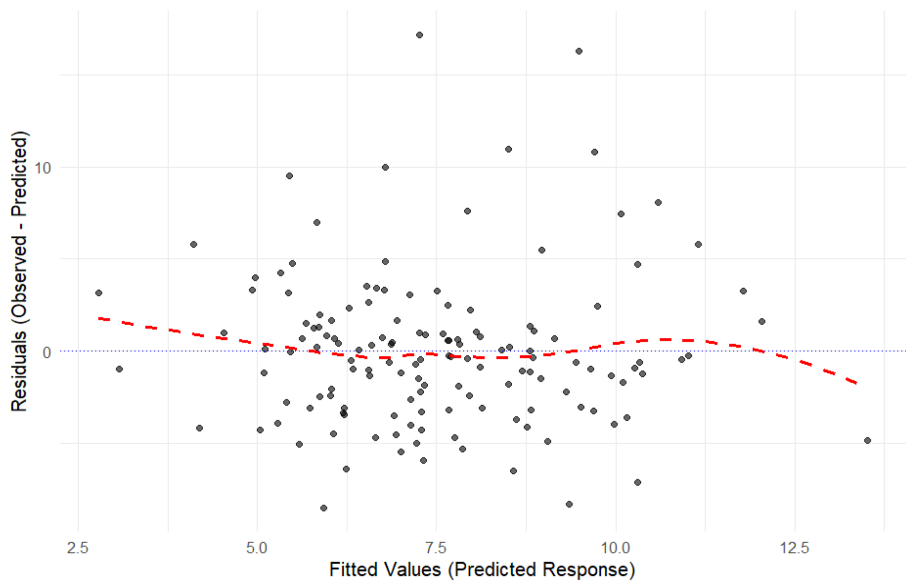
Robustness checks are also performed on Model 2 to improve the internal validity of the thesis. While high multicollinearity was detected in Model 1, no variables exhibit high or moderate multicollinearity in Model 2. These results are seen in Table 9, where the adjusted GVIF score for entity_categoryfactorGCF is below the standard thresholds for multicollinearity. The variables with one DF also have GVIF scores all below the thresholds for moderate multicollinearity (5) and high multicollinearity (10).

Table 9: Multicollinearity Scores of GCF

Variable	GVIF	Df	$GVIF^{(1/(2*df))}$
entity_categoryfactorGCF	1.698	2	1.141
avg_climate_adaptation_score	3.163	1	1.778
avg_civil_score	1.129	1	1.063
avg_fcs_score	3.328	1	1.824
DurationGCF	1.125	1	1.061
Financing_disbursedGCF	1.149	1	1.072
author_numericGCF	1.055	1	1.027
Project_per_countryGCF	1.272	1	1.128
Project_per_EntityGCF	1.349	1	1.161

Using the Breusch-Pagan test to measure heteroskedasticity in Model 2 produces a p-value of 0.498, greater than the chosen p-value of 0.10 in Model 2. This absence of heteroskedasticity is confirmed in Figure 22 where the red dotted line, denoting the trend of residuals across the range of fitted values remains consistently close to 0 and shows limited fanning out. As found in Model 1, Model 2 does not find evidence of heteroskedasticity meaning the residual errors in the model are correct.

Figure 22: Residuals vs. Predicted Values in Multiple OLS Regression of Model 2



The following chapter will discuss the potential causal mechanisms behind the contrasting results found in Models 1 and 2.

Chapter 5: Discussion

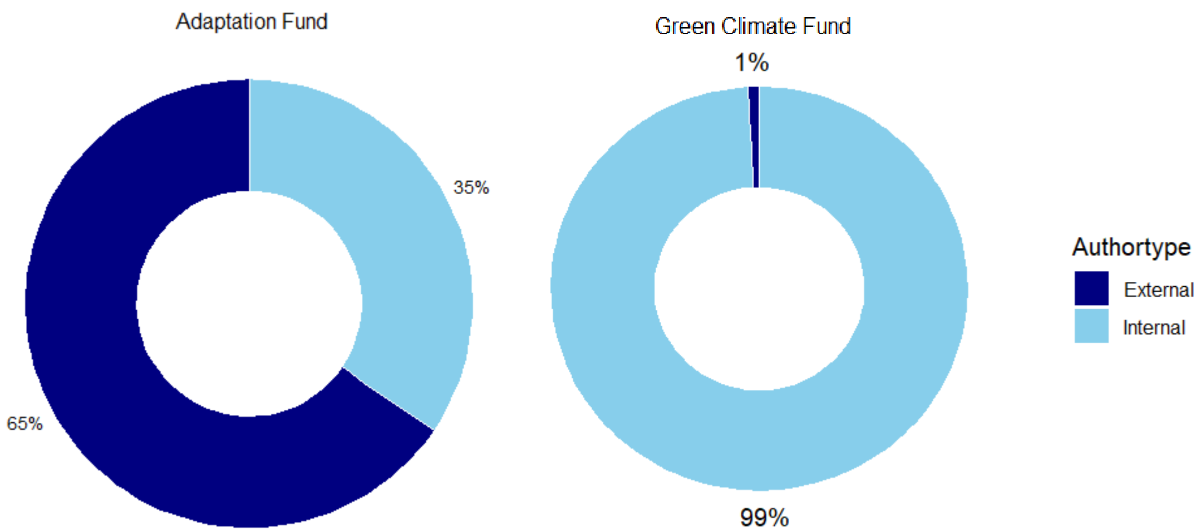
While Model 1 partially supported the theoretical expectations of H1, partially rejecting H0, Model 2 rejected both H1 and H0. The differences in these results can be explained by a potential causal mechanism: the contrasting structures of the AF and GCF, measured by varying independence of fiduciary management, financial capacity, and different formats of AF and GCF project documents.

5.1 Implementing Entity Types in Model 1

Revisiting the structure of the AF helps to explain the significance of the relationship between international implementing entities and sentiment score surrounding local inclusion rhetoric in Model 1. Regarding financial capacity, the AF disbursed 1.2 billion USD, or 14 billion USD less than the GCF in project implementation (Adaptation Fund, 2024a; Green Climate Fund, 2025b). Funding disbursement is highly concentrated in the UNDP, World Bank, UN World Food Program, and UN Environment Program, or roughly one-third of the AF's total disbursed funding for completed projects (376.6 million USD of 1.2 billion USD), as seen in Chapter 3 Figure 7. The funding disbursement pattern illustrates a preference of the AF to use more international implementing entities in large-scale projects. This financial relationship exhibits trust between the AF and international implementing entities, increasing the AF's susceptibility to local inclusion norm diffusion. The fiduciary management of the AF also perhaps makes it more dependent on international implementing entities than the GCF. The World Bank not only acts as a trustee of the AF in terms of managing the limited public and private donations it receives but is also responsible for the monetization of the certified emissions reductions to support the AF (Adaptation Fund, 2019). As the legal owner of the trust fund for the Adaptation Fund, the World Bank administers the fund's assets and receipts. While the World Bank still reports to and cooperates with the AF, its reputation, experience, and size greatly surpass the AF, allowing hierarchical dynamics to expose the AF and its working bodies to international implementing entity norm diffusion. Further, the AF only has a secretariat of less than 20 staff (Adaptation Fund, 2024e), limiting the available expertise and knowledge to approve projects and support implementation. These weaker structural characteristics demonstrate how the AF is more receptive to norm diffusion.

Regarding project documents, the AF corpus consists predominantly of final evaluation reports. Using a narrative-based analysis, most final evaluation documents include traditional report sections such as an assessment of project outcomes and lessons learned. The storytelling style of these documents allows for more flexibility in language choices, rather than filling out a form, for example (Jasleen & Saini, 2014). This style of writing also encourages more expressive language, allowing international implementing entities to more easily pressure authors to infuse positive sentiment in final evaluation reports. While the author type variable did not have a statistically significant relationship with sentiment score for Model 1, Figure 20 in Chapter 4 shows the high propensity of international implementing entities to use external authors. As component of the AF project document format, authorship and the underlying association with international implementing entity can help explain significance of international implementing entity type on sentiment score in Model 1.

Figure 23: Author Type Distribution based on Filtered Project Documents for the AF and GCF



Of all the final evaluation reports written, 65% are written by sources external to the AF, such as a hired independent evaluator or consultant, as seen above in Figure 23. External authors are traditionally considered more neutral; however, the reputation and expertise of international implementing entities such as the UNDP and World Bank still visibly impacted the framing of local inclusion in Model 1. Conversations and research undertaken by independent evaluators most likely encountered the exploited norm of local inclusion, where international implementing entities present themselves as more supportive of local inclusion as reflected in positive sentiment towards local inclusion rhetoric. The socializing power of these international implementing entities within the AF allows them to reinterpret the local inclusion norm. This reinterpretation occurs where local inclusion is perceived more positively despite potentially misrepresenting genuine local inclusion. By doing so, international implementing entities improve their reputation, reinforcing their influence in MCFs. It is also important to note that while the project documents for the AF are authored by external consultants, these external reviewers are often selected by international implementing entities themselves. This working relationship can lead to potential selective hiring processes, allowing authors to support international implementing entities' agenda in imbuing the AF with the local inclusion norm that portrays international implementing entities more positively. The authors' reports are also made public based on the final approval of the AF, illustrating how the AF accepts normative language adopted in favor of international implementing entities' positive sentiment towards local inclusion rhetoric. Therefore, while external authors are assumed to be neutral, there is still flexibility for prominent reputations and existing bias to support international implementing norm diffusion. Project document format as a structural dimension of the AF shows how project document characteristics, including narrative style writing and external authorship, in the AF corpus increase the AF's receptiveness to norm diffusion by international implementing entities.

Regarding regional and national direct-access entities, these entity types did not have a statistically significant impact on the sentiment score of project documents in Model 1. Regional entities, however, were only represented by one project, making it difficult to establish any sort of relationship as seen in Figure 4 in Chapter 3. National direct-access entities did not impact sentiment surrounding local inclusion as the use of these entities is most likely expected to automatically support local inclusion. The assessment of local inclusion is perhaps less likely to be as rigorous because the accreditation process for these entities assumes local inclusion is already addressed (Mathur-Filipp & Bista, 2015; Green Climate Fund, 2011). While the literature (Alcañiz & Giraudy, 2023; Omukuti, 2020) warns against the assumption of locality for direct-access entities, as government ministries, for example, can hijack project outcomes to serve their vested interests, Model 1 shows that national direct-access entities do not significantly impact sentiment surrounding local inclusion positively or negatively.

5.2 AF Entity Case Comparison

Zooming in further, comparing AF projects that are implemented by international versus national direct-access entities offers additional insights into their relationship, or lack thereof, with sentiment score surrounding local inclusion rhetoric. Adopting a most-similar case approach, two AF projects in Argentina were selected: "Increasing Climate Resilience and Enhancing Sustainable Land Management in the Southwest of the Buenos Aires Province" implemented by the World Bank (International Bank of Reconstruction and Development) and "Enhancing the Adaptive Capacity and Increasing Resilience of Small-size Agriculture Producers of the Northeast of Argentina" implemented by Unidad Para Cambio Rural Argentina (UPCRA) (Moreyra, et al., 2020; Avila, 2019). Both these projects were implemented with similar budgets, 4,296,817 USD for the World Bank and 5,640,000 USD for UPCRA, and in similar project areas, rural development and agriculture, lasting roughly four years. The World Bank's average sentiment score is 12.947 per page, and the UPCRA project document's sentiment score is 4.537, offering an example of the relationship observed in Model 1 where international implementing entities have a more positive sentiment score surrounding local inclusion rhetoric than national direct-access implementing entities. The project characteristics are summarized in Table 10 below.

Table 10: AF Entity Case Comparison

Project	**Increasing Climate Resilience and Enhancing Sustainable Land Management in the Southwest of the Buenos Aires Province**	**Enhancing the Adaptive Capacity and Increasing Resilience of Small-size Agriculture Producers of the Northeast of Argentina**
Funding Allocated	4,296,817 USD	5,640,000 USD
Accredited Implementing Entity	World Bank	Unidad Para Cambio Rural Argentina (UPCRA)
Implementing Partner	Ministry of Environment and Sustainable Development	Secretariat of Environment and Sustainable Development, National Secretariat of Agroindustry, and National Institute for Agriculture Technology
Project Status	Completed 2015-2019	Completed 2013-2018
Author	Alejandra Moreyra (Ministry of Environment and Sustainable Development Contact) Vanina Pietragalla (Ministry of	Penelope Vaca Avila (Consultant)

	Environment and Sustainable Development Contact) Tuuli Bernardini (World Bank Contact	
Beneficiaries reached	3,536	4,000
Country Characteristics	Average Civil Society Score: 0.863 Average Climate Adaptation: 48.811 Average Fragile Index: 47.092	
Sentiment score per page	12.947	4.537
Type of project/sector area	Adaptation: Rural Development	Adaptation: Food Security

The AF project in the Buenos Aires Province, implemented by the World Bank, expressed positive statements in the project summary document surrounding local inclusion rhetoric with phrases such as “strong ownership of key local actors” (Moreyra, et al., 2020, p. 10), “successful initiatives” (Moreyra, et al., 2020, p. 4), and “strong local presence” (Moreyra, et al., 2020, p. 9). These statements emphasize how the internally written project completion report portrayed local inclusion as integral to the project’s success and was therefore overwhelmingly portrayed as positive. The necessity placed on local inclusion shows how international implementing entities continue to perceive local inclusion as positive to address non-state actors' historical concerns of IOs’ exclusionary practices in development. Criticism of the World Bank and its implementing decisions as well as project-specific context, such as the current economic situation faced by beneficiaries, were absent from the document. While implemented by an international implementing entity, the project document was written internally and cannot support or disprove the association between external authorship impacting sentiment score proposed in Chapter 4 with Figure 20.

The AF Project in Northeast Argentina, implemented by UPCRA, on the other hand, is a final evaluation report written externally. This report expresses sentiment surrounding local inclusion in statements such as “country ownership was high” (Avila, 2019, p. 9) and “used prioritized and strengthened local knowledge” (Avila, 2019, p. 28). Overall, the report presents the projects’ outcomes as “satisfactory” or “highly satisfactory,” however, the negative sentiment stems from the description of the "worsening" and "unfavorable" socio-economic conditions of the beneficiaries given the political and economic climate during the project duration (Avila, 2019, p. 44). This context confirms the faction of literature that emphasizes national direct-access entities are more likely to discuss problems or concerns regarding local inclusion because their local affiliation already appears to satisfy the requirement of locality (Colenbrander et al., 2018; Browne, 2022). Direct-access entities seem more likely to discuss local inclusion sentiment negatively because they are not as pressured to conceal risks. There is also a risk that despite being authored externally, the external consultant is biased towards UPCRA, depending on the author's nationality and working relationship (Avila, 2019). This fledgling status may encourage overly positive sentiment surrounding local inclusion throughout the report to ensure a continued working relationship with the AF and mask risks of marginalization and the vested interests of local stakeholders (Price, 2021; Alcañiz & Giraudy, 2023; Omukuti, 2020). The relationship between direct-access entities and sentiment score, however, is not significant in Model 1, perhaps because direct-access entities lack the same reputational weight and credibility that UN and Bretton Woods Institutions use to manipulate the climate finance agenda. The lack of a statistical relationship may also be due to the limited number of observations included in Model 1. Nonetheless, examining quotes from the project documents of an international implementing entity and national direct-access entity is illustrative of how more positive language surrounding local inclusion is adopted in international implementing entity-led projects, providing evidence of international implementing entity norm diffusion in MCFs.

5.3 Implementing Entity Type Model 2

Looking at the GCF structure tells a different story to support the findings of Model 2. As of December 2024, the GCF approved nearly 15.9 billion USD in funding for projects, demonstrating a stronger financial capacity and project scalability (Green Climate Fund, 2025b). Regarding ongoing projects, international implementing entities tend to distribute the largest project budgets, such as the World Bank, UNDP, and Agence Francaise de Developpement, which distributed a total of 2.8 billion USD, as seen in Chapter 3 Figure 8. While international implementing entities also distribute the largest amounts of funding in the AF, the GCF appears to exhibit more organizational autonomy in directing project narratives. In Gehring and Vizitiu's (2024) study, they found that the policy-guiding organizational rules adopted by the GCF offer clear guidelines and decision-making, which incentivize member states to adhere to GCF financial policies. While board members or member states objected to certain funding decisions, the GCF maintained a semblance of authority, executing decisions in the best interest of the organization rather than the interests of members. Therefore, the GCF's credibility, established in policy frameworks, granted it more decision-making authority. While their study focused on member state preferences in financial decision-making, it can still be used as an indicator, along with Model 2's findings, to support the claim that the GCF maintains organizational autonomy from prominent IOs in project implementation as well. This organizational autonomy demonstrates how the GCF can resist international implementing entities' attempts to diffuse self-serving local inclusion norms, instead acting as its own norm entrepreneur.

This organizational autonomy in the GCF's structure is based not only on its financial capacity but also on the independence of its fiduciary management and stronger technical expertise. Nilsson (2017) asserts that intergovernmental organizations can significantly influence norm cycles with their technical expertise and experience, clearly defining solutions to established problems. While an MCF rather than an IGO, this study's findings still suggest the GCF's technical expertise and credibility allow it to not only maintain organizational autonomy from IOs but use its technical expertise to influence norm cycles. This technical expertise is supported by its vast resources, including its secretariat of 300 staff members working in 17 different departments, each relying on specialized working knowledge to execute their tasks (Green Climate Fund, 2025c). The AF, on the other hand, has a secretariat of 15-20 members (Adaptation Fund, 2024e). The GCF also relies on more diversified sources for funding than the AF, allowing it more flexibility and independence in fiduciary management (Green Climate Fund, 2011). The GCF's technical expertise and fiduciary management encourage GCF to oppose bureaucratic and member-state interests and restrict international implementing entities' norm diffusion capabilities.

The GCF's organizational autonomy is also evidenced by the structure of the GCF's project document structure used in Model 2. The annual project summary documents and occasional final evaluation reports are mostly authored internally (99%) by a representative of the accredited implementing entity, as seen in Figure 23, illustrating no association between author type and implementing entity type. The annual project summary documents include a rigid format for entities to fill out including sections such as implementation status, project progress, core indicators, project outcome indicators, as well as social and environmental safeguards. The format of these documents, therefore, restricts international implementing entities' ability to curate more positive sentiment towards local inclusion. They are rather expected to fill out the form accordingly based on metrics rather than use descriptive analysis to discuss project progress. While positive sentiment towards local inclusion rhetoric is adopted in these project summary documents, Table 5 in Chapter 4 shows that there is no relationship between implementing entity type and sentiment score in Model 2. International implementing entities may try to more heavily emphasize their commitment to local inclusion by exploiting the local inclusion norm, yet the GCF seems to diffuse an alternative version of the local inclusion norm. This environment of positive local inclusion is most likely born out of the institutional innovations the GCF has come to be associated with (Kalinowski, 2024), creating a reputation based on positive engagement and inclusive practices. International implementing entities struggle to compensate for their previous stakeholder exclusion in the GCF because the GCF creates an environment of positive local inclusion. There is also no statistically significant relationship with regional and national-direct access entities on sentiment score, illustrating how the GCF can restrict sentiment score for each entity type. International implementing entities, therefore, cannot position themselves as ambassadors of positive local inclusion narratives, nor can regional or national direct-access entities impact sentiment score, because the GCF itself emphasizes local inclusion in its structures. Rather than endorsing the local inclusion norm of international implementing entities, which positions them in a more favorable light, the GCF acts as its own norm diffuser.

5.4 Significance of Additional Variables

The significance of additional variables in Models 1 and 2 must also be further explained. In both models, the projects per entity variable has a statistically significant relationship with the sentiment score surrounding local inclusion rhetoric. In Model 1, however, when projects per entity increases by one and all other variables are held constant, sentiment score decreases by 0.220, whereas in Model 2, it increases sentiment score by 0.131 for every additional project per entity when all other variables are held constant. A few possibilities can explain the different effects of this variable on the models. In Model 1, as entities manage more projects, project authors might find that implementing entities have insufficiently addressed local inclusion needs, creating a more negative sentiment of local inclusion rhetoric. Depending on the capacity of the entity, some entities, for example, may lack expertise in agricultural projects compared to forestry-based projects, unable to successfully execute projects inclusively in all sector areas. More projects implemented by entities also increase exposure to problems such as the inability to address community needs or equitably include stakeholders. The increased likelihood of problems, therefore, may contribute to a more negative sentiment surrounding local inclusion rhetoric. In Model 2, as entities manage more projects, sentiment score positively increases, perhaps showing implementing entities' capacity to address problems in different contexts and apply these learning outcomes throughout the implementation period. As most documents are written internally and expected to follow the same format, entities might also adopt similar positive sentiment across projects to meet the annual report summary form requirements. Therefore, the different impacts of the projects per entity variable on sentiment score are due to the potential intervening variables of the structure of project documents and experience of implementing entities.

In Model 2, project duration is also significant, which appears logical. When all other variables are held constant, as the number of years a project lasts increases by one, sentiment score decreases by -0.546. A longer project implementation period allows more problems, risks, and setbacks to occur. Therefore, duration negatively impacts sentiment score in Model 2 because more local inclusion problems will inevitably occur over time, such as failing to address various recipient needs, poor communication with stakeholders, and exposure to additional social and environmental risks. At the same time, longer projects could invite more opportunities for local collaboration and inclusion, increasing positive sentiment. However, as the results significantly show an inverse relationship between duration and sentiment score, this is not the case and perhaps can be investigated with further research. In Model 1, project duration also negatively impacts sentiment score by -0.667 but does not occur in enough observations to be statistically significant.

5.5 GCF and AF Case Comparison Analysis

As the structural differences between the AF and GCF seem most likely to account for the contrasting results of Models 1 and 2, a brief project comparison is helpful to understand the norm diffusion capacities of each fund in the realm of climate finance. The projects, summarized in Table 11 below, were selected using a most similar criterion to magnify the underlying differences accounting for the impact on sentiment score of local inclusion rhetoric. The selected projects take place in Egypt and Mauritania, countries with similar vulnerability and adaptive capacities to climate change along with state fragility. Egypt, however, scores lower on the civil society score most likely due to its authoritarian rule and history of repressing political dissidents (Yefet & Lavie, 2021). Both projects are implemented by UN agencies: the UN Development Program (UNDP) in Egypt and the UN World Food Program (WFP) in Mauritania. Both projects are also adaptation-focused, which assumes a positive expression of local inclusion due to the direct impact on beneficiaries. The GCF "Enhancing Climate Change Adaptation in the North Coast and Nile Delta Regions in Egypt" project entails two components. These include decreasing the vulnerability of coastal infrastructure and assets through improved construction as well as the development and implementation of a coastal zone management plan (Afaneh, 2024, p. 3). The AF "Project for Enhancing Community Resilience and Food Security to Adverse Effects of Climate Change in Mauritania" had three objectives including improving community capacity and technical services, designing adaptation measures against desertification and land degradation, and implementing measures to diversify food resources (Saadani & Selmane, 2019, p. 15). To implement these projects, both accredited entities also relied on national executing entities, namely government ministries. Despite these similarities, the sentiment score for the GCF Egypt-based project was 5.02 per page, a sentiment score not impacted by implementing entity type as seen in Model 2, while the sentiment score for the AF Mauritania-based project was 15.7, a score impacted by international implementing entity type as seen in Model 1. Analyzing these projects with a most similar case comparison can, therefore, reveal international implementing entities' ability to diffuse the local inclusion rhetoric norm, as expressed in positive sentiment score, in different AF and inability to do so in the GCF.

Table 11: AF and GCF Project Comparison

Project	**Enhancing climate change adaptation in the North coast and Nile Delta Regions in Egypt (GCF)**	**Project for Enhancing Community Resilience and Food Security to Adverse Effects of Climate Change in Mauritania (AF)**
Location	Dakhelia, Behira, Damietta, Portsaid, Kafr El-Sheikh	85 villages in southern Mauritania targeted, areas where food insecurity is highest
Funding Allocated	31.3 million USD	7.8 million USD
Accredited Implementing	UN Development Program	UN World Food Program

Entity		
Implementing Partner	Ministry of Water Resources & Irrigation	Ministry of Environment and Sustainable Development
Project Status	Ongoing 2018-2026	Completed 2014-2019
Author	Ahmad Afaneh (UNDP Contact)	Youssef Saadani and Mohamed Lemine Selmane (Consultants)
Beneficiaries	17,240,000 (expected reach)	78,000 reached
Country Characteristics	Average Civil Society Score: 0.198 Average Climate Adaptation: 46.58 Average Fragile Index: 87.8	Average Civil Society Score: 0.459 Average Climate Adaption: 38.1 Average Fragile State Index: 90.6 Economy based on subsistence of livestock and agriculture in addition to extractive industries and industrial fishing.
Sentiment score per page	5.02	15.7
Type of project/sector area	Adaptation: Coastal Infrastructure	Adaptation: Food Security

A brief content analysis confirms the interpretation of the multiple OLS regressions in which the structure of the MCFs informs the contrasting sentiment scores. The AF project based in Mauritania was completed in 2019 and was one of the AF's first projects as well as the WFP's first project with the AF, predisposing implementation towards positive sentiment. An initial project most likely hopes to appear more positive to encourage future partnerships and improve the MCF's reputation. Therefore, the AF was more malleable in its earlier stages to the local inclusion norm diffusion by the WFP as both mutually benefited from a positive reputation and strong success rate. As a completed project, the AF project document is a final evaluation report, written by external consultants hired by the WFP. Due to this working relationship, there is a potential bias of the consultants towards the WFP depending on their working history, a history that would most likely be absent if the AF intervened in the hiring process. To gather their findings, these consultants relied on project documentation, site visits, and stakeholder interviews (Saadani & Selmane, 2019). The report includes an executive summary, assessment of project components, risk management, and lessons learned, all expected sections to appear in a final evaluation report. The narrative style of the report allows for flexibility in how sentiment surrounding local inclusion is perceived in an MCF already more prone to norm diffusion due to its dependent fiduciary management, as well as limited financial capacity and expertise. Examples of this sentiment are expressed as follows: "strong social cohesion" (Saadani & Selmane, 2019, p. 9), "strong sense of ownership" (Saadani & Selmane, 2019, p. 32), "significant benefits in terms of empowerment and strengthening of organizational and productive capacities of women" (Saadani & Selmane, 2019, p. 31), and "the project is performing satisfactorily" (Saadani & Selmane, 2019, p.10), underlined in the document for emphasis. The project document's characteristics show how the WFP presented local inclusion more positively in the weaker structured AF, obscuring potential risks and contradictions during project implementation.

These contradictions are seen in the assessment of the project's partnerships. While the implementing and executing entities are praised for "effective coordination between all stakeholders" (Saadani & Selmane, 2019, p. 23), stating "the project's commitments to the communities and the partners involved are in vast majority honored" (Saadani & Selmane, 2019, pp. 9-10), the largest risk the project encountered was its sustainability due to a lack of locally built partnerships. The authors stated concerns of longevity as the project's success was largely dependent on the WFP's involvement and resources, whereas the inclusion of regional services and institutional succession appeared to be deprioritized (Saadani & Selmane, 2019, p. 43). This criticism of project sustainability still seems to be overshadowed by the positive assessment of community and stakeholder inclusion throughout the report, illustrating the WFP's ability to distill the local inclusion norm through its reputation and credibility as an international implementing entity. This norm diffusion capacity is further evidenced by the discussion of project risks, limited to the duration of capacity training for technical services and the sustainability of the project's success after its official end. Risks of exclusion based on local hierarchies among ethnic groups and how they could be combated were absent. Instead, gender mainstreaming appeared to be used as a proxy for local inclusion of societal groups (Saadani & Selmane, 2019, p. 31), a concept born out of the UN Economic and Social Council report in 1997 (United Nations Economic and Social Council, 1997), providing further evidence of international implementing entities' abilities to diffuse norms in project implementation. There is also no mention of a redress or grievance mechanism for beneficiaries to access during the project duration creating obstacles for beneficiaries to voice criticism and concerns. Hierarchical differences between beneficiaries and the consultants hired by the international implementing entity may have also created boundaries preventing local community members from voicing any tensions or social risks caused by the project's implementation. The limited criticism and space for criticism provide evidence of the WFP diffusing the international implementing entity version of the local inclusion norm within the AF, presenting positive sentiment while potentially ensconcing marginalization and discrimination. While the lack of criticism may be due to the project's status as one of the first implemented projects of the AF incentivizing a positive framework, the limited criticism of the WFP itself shows the socializing powers of international implementing entities in weaker structured MCFs such as the AF.

The GCF structure, on the other hand, directly contrasts with the AF, impacting implementing entities' ability to diffuse norms, as measured with sentiment score. The GCF project began in 2018 and is still ongoing. Because of its ongoing status, it is most likely written internally to save costs on contracting a consultant annually to complete the project summary report. As the annual project summary report is authored by the UNDP contact, it is expected that the UNDP would easily imbue positive sentiment into local inclusion rhetoric. However, as explained in the earlier sections of this chapter, the fiduciary management, financial capacity, and technical expertise of the GCF create a more controlled environment, which is only further supported in the structure of the GCF project document. Model 2 also revealed no statistically significant relationship between author type and sentiment score. While the AF project document was written in a report style relying on a mixed methods approach, the GCF project uses a form relying on quantitative metrics and pre-written answers for its assessment. Each project objective, for example, is accompanied by a specific project activity and the activities' implementation progress, which is written as a percentage without specific criteria to define how progress is calculated (Afaneh, 2024, p. 10). Measurements of local inclusion also largely focus on the number of people reached and the number of beneficiaries who are women rather than the different socio-economic classes or ethnic groups reached and why (Afaneh, 2024, p. 13). The risks addressed included both technical risks, such as project deliverable delays, as well as social and environmental risks, such as environmental risks associated with construction and concerns of

Covid-19 (Afaneh, 2024, p. 24). These risks are included as the form requires a section on Environmental and Social Safeguards and Gender to be filled out (Afaneh, 2024, p. 24). The GCF form also requires a section on how the implementing entities publicize the grievance mechanism to beneficiaries, forcing the UNDP to describe the inclusion of its accountability and compliance units into project implementation (Afaneh, 2024, p. 25). Therefore, the GCF institutionalizes a favorable version of local inclusion into its structure based on the stipulated requirements incorporated into annual project summaries.

Because of the more metric-based approach, there is a limited discussion on local inclusion and a paucity of reflective quotes. In terms of the Gender Action Plan, where women were contracted to build reed fences in construction sites, their involvement was seen as “providing social benefits” (Afaneh, 2024, p. 29). One specific project in Kafr El Sheikh reported “high level of outreach to local community” (Afaneh, 2024, p. 29). Yet the positive local inclusion language adopted in the AF project is largely absent from the GCF project document. Using prescribed language and quantitative indicators limits extreme sentiment regarding local inclusion rhetoric in project implementation. The style adopted in the GCF annual project summary document, therefore, indicates how the GCF diffuses a reinterpreted version of the local inclusion norm where inclusive practices are expected among all implementing entities, preventing specific entities, such as international implementing entities, from presenting themselves as overly positive towards local inclusion. At the same time, this allows the GCF itself to improve its reputational standing in climate finance, potentially obscuring how local inclusion unfolds on the ground.

Based on this case comparison on the content of the GCF project in Egypt and the AF project in Mauritania, the causal mechanisms determining local inclusion sentiment all relate to the MCFs’ structural differences. The varying strength of these MCF structural components concerning fiduciary management, financial capacity, and technical expertise and project document structure impact implementing entities’ ability to diffuse norms, as measured by sentiment score. The robust GCF and its controlling environment require strict project documents with metric-based indicators, further limiting sentiment surrounding local inclusion rhetoric. The weaker structured AF, on the other hand, allows for more flexibility in its final evaluation reports, encouraging sentiment surrounding local inclusion rhetoric. The findings of the most similar case comparison also show that gender is often used as a proxy for local inclusion, despite gender only accounting for one indicator of local inclusion. These MCFs emphasize gender policies and frameworks but take an apolitical approach to assessing local inclusion and expressing sentiment, as is expected of international implementing entities (Skovgaard et al., 2023). Rather than detail which ethnic groups were involved and why, the average age and education of beneficiaries, or how many beneficiaries came from differing socio-economic classes, narrative and metric analyses focused predominantly on gender. The results of the most similar case comparison, in combination with the results from the multiple OLS regressions, are summarized in Figure 24 below.

Figure 24: Norm Diffusion Pathways in the AF and GCF

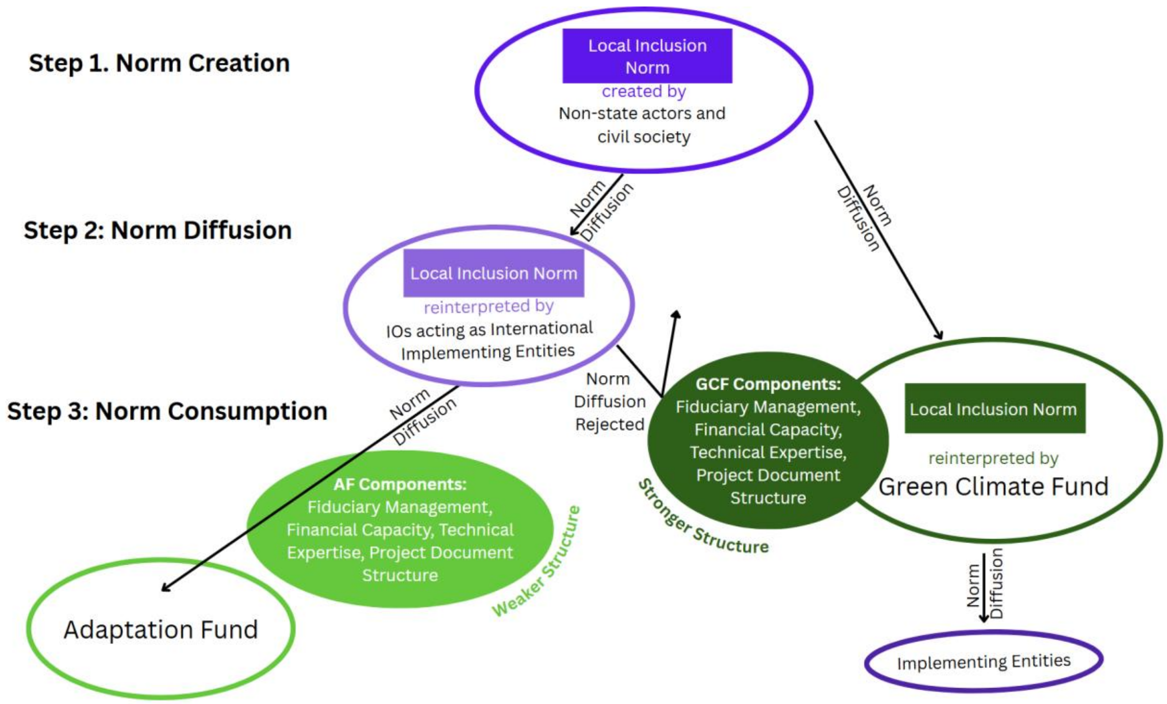


Figure 24 begins with norm creation. As discussed in Chapter 2, the local inclusion norm was created by non-state actors and civil society as IOs failed to adopt inclusive practices in development projects. This norm was diffused and adopted by IOs working as international implementing entities in climate finance as well. Rather than genuinely adopt local inclusion practices, international implementing entities reinterpreted this norm, claiming to express positive sentiment towards local inclusion rhetoric in project implementation even if marginalization and exclusion were present. International implementing entities successfully diffused this reinterpreted norm in the AF due to the AF's weaker structure. The AF's consumption of this norm is supported by its limited financial capacity, technical expertise, more dependent fiduciary management, and expressive project document structure, all of which suggest the AF's receptiveness to norm diffusion. International implementing entities express more positive sentiment towards local inclusion rhetoric than direct-access entities, using this positive sentiment to position themselves as dutiful and benevolent.

In the context of the GCF, the diffusion of international implementing entities' reinterpreted local inclusion norm is rejected due to the GCF's stronger structure. The GCF exhibits organizational autonomy as a result of its empowered fiduciary management, financial capacity, technical expertise, and template-structured project documents. With this more robust structure, the GCF consumes the local inclusion norm from non-state actors and civil society as the GCF was created and intended to be supportive of local inclusion, evidenced by its number of institutional innovations (Kalinowski, 2024). Yet the GCF also reinterpreted this local inclusion norm. Rather than allow international implementing entities to position themselves as more inclusive, or allow other implementing entities to dictate sentiment, the GCF created a strong socializing environment where the GCF presents itself as more locally inclusive. This norm is diffused to all implementing entities ensuring no single implementing entity appears more supportive of local inclusion than other entities, but rather the GCF as a whole is perceived as supportive of local inclusion, concealing exclusionary practices executed on the ground. Again, the same contradiction arises where actors use the local inclusion norm to support their reputation while obscuring genuine local inclusion, but in the context of the AF, its international implementing entities presenting themselves more positively towards local inclusion and in the context of the GCF, it is the GCF itself.

This analysis helps to explain why Model 1 partially supported H1 and H0 while Model 2 rejected both H1 and H0 as there are fundamental differences in the MCFs' structures, which can function as different entry points of norm diffusion whether from the international implementing entity perspective in the case of the AF or MCF perspective regarding the GCF. These findings can also be generalized for studies on MCFs as the findings illustrate how power derived from fiduciary management, financial capacity, technical expertise, and project document structure impacts the ability of MCFs to act as norm consumers or diffusers when interacting with international implementing entities. The relevance of these findings for norm diffusion and consumption in the context of climate finance is explored further in the conclusion.

Chapter 6: Conclusion

6.1 Contributions

The Adaptation Fund and Green Climate Fund are the only two multilateral climate funds working to alleviate the complexity of climate finance and improve financial flows with direct-access entities. At least, this is the narrative that is publicized. Removing unnecessary intermediaries and allowing national and subnational actors to access and disburse grants can improve the effectiveness of climate finance, yet understanding how local inclusion is perceived in project implementation is also an understudied but important indicator of who is controlling project narratives and why. While direct-access entities are considered local based on their status and knowledge, international implementing entities are incentivized to exaggerate positive sentiment towards local inclusion to counter their previous reputations of neglecting diverse stakeholders in project implementation. These behavioral expectations are informed by the theoretical lens of norm diffusion, in which IOs can act as propagators of norms based on their bureaucratic expertise and reputation or as consumers of norms, where nonstate actors use praise or criticism to dictate the behaviors and practices of IOs (Park 2005; Martins and Simmons, 2012; Finnemore & Sikkink, 1998). This theory sought to answer the research question: *How does the type of implementing entity impact sentiment surrounding local inclusion in project implementation*? In response, H1 expected international implementing entities to encourage more positive sentiment than other implementing entities. While Model 1 of the multiple OLS regression partially confirmed H1, Model 2, based on GCF project documents, rejected both H1 and H0, providing two novel contributions to the existing literature.

First, analysis of the AF project documents in Model 1 shows international implementing entities' ability to act as norm diffusers in weaker structured MCFs. Establishing a relationship between international implementing entities and sentiment score confirms the norm diffusion capacity of these entities in the context of a weaker MCF, which is rarely analyzed in the literature. Instead, existing literature focuses on how international implementing entities are often preferred in project implementation for their financial expertise, management, and reputation (Fenton, et al., 2014), while these same entities assume apolitical approaches in their execution, marginalizing communities and prioritizing donor interests over beneficiaries' needs (Browne, 2022; Skovgaard et al., 2023). Positive sentiment towards local inclusion rhetoric in project implementation shows how international implementing entities can use their reputation and experience to diffuse the reinterpreted local inclusion norm, promoting the implementing entity's standing and obscuring actual stakeholder inclusion. While a more positive sentiment towards local inclusion can reflect successful local inclusion during the project's duration, this sentiment adopted by international implementing entities seems exaggerated to address civil society concerns of exclusionary practices. International implementing entities can enforce this reinterpreted local inclusion norm as the AF is more malleable to norm diffusion, as concluded in Chapter 5 Figure 24. The weaker financial capacity, technical expertise, and less independent fiduciary management of the AF alongside the narrative-based final evaluation reports all make the AF more vulnerable to international implementing entities' version of the local inclusion norm. Therefore, this thesis adds a necessary quantitative assessment to the field of climate justice and climate finance. As international implementing entities impact sentiment score more positively than national direct-access entities in the context of the AF, this statistically significant relationship helps to infer existing power dynamics in the climate finance regime and, as a result, who is driving local inclusion narratives.

Second, Model 2's findings show that MCFs can also act as norm diffusers, connecting the fields of climate finance and norm diffusion, which remains largely understudied. While implementing entity type did not show a statistically significant relationship with sentiment score in Model 2, the discussion of the results, existing theory, and the most similar case comparison offer evidence of the MCF's varying structural components as the causal mechanism informing the contrasting results of Models 1 and 2. As established in the discussion of the results, the GCF's knowledge, management, capacity, and project document structure allow it to assume the role of norm entrepreneur, setting the agenda for local inclusion rather than allowing implementing entities to use perceived sentiment of local inclusion to their advantage. While existing theories of norms do support the GCF as organizationally autonomous in financial decision-making (Gehring & Vizitu, 2024), this thesis shows the GCF also orchestrates independence in project implementation. The most similar case comparison of the GCF project in Egypt and the AF project in Mauritania further illustrated how the structural components of the GCF facilitated the GCF as a norm entrepreneur. The GCF prevents international implementing entities from exploiting the local inclusion norm, instead diffusing their version of the local inclusion norm to implementing entities that promotes the GCF's positively perceived identity of supporting local inclusion. Similar to international implementing entities' exploitation of the local inclusion norm, the GCF also seems to advance its reputation through perceived positive local inclusion, while discriminatory practices may unfold on the ground. Understanding MCFs as norm diffusers shows their capacity to shape project implementation outcomes to the fund's best advantage, supporting or potentially obscuring genuine local inclusion.

These findings also offer policy and societal contributions. As international implementing entities impact sentiment surrounding local inclusion in the AF and the GCF itself directs the diffusion of local inclusion norms, more rigorous assessments are required in project evaluation and annual summary reports to understand how stakeholders are truly engaged. The AF, for example, must place more emphasis on its redress mechanism to ensure beneficiaries understand what resources they have access to. As of December 2024, no active complaints were processed by the Adaptation Fund Redress Mechanism, while the GCF's independent redress mechanism has processed 14 cases (Adaptation Fund, 2024d; Independent Redress Mechanism, 2025). This discrepancy may be due to the scale or number of projects implemented but is also most likely impacted by the AF's failure to adequately publicize its redress mechanism during project implementation. Interviews with beneficiaries, in addition to project managers, should also be more actively included in reporting based on time and availability. The AF should also assess the credibility of hired consultants to ensure there is no established working relationship or potential for bias between the consultant and international implementing entity. Regarding the GCF, their strict annual project summary form allows for a concise overview of project progress but provides minimal room to explore risks to communities and how beneficiaries assess their inclusion. Adding a survey component or interview section would help corroborate the statistical indicators implementation progress relies on. Detailing the rationale behind the implementation progress metric would also provide further understanding as to what the project's priorities are and what obstacles are preventing the project from making inroads. These additional components can offer more robust measures of local inclusion during project implementation in the AF and GCF.

In terms of societal contributions, understanding the pathways to diffuse local inclusion norms in climate finance further reveals the risks of exaggerated positive sentiment towards local inclusion in rhetoric. International implementing entities in the AF can use their influence to potentially conceal which social-ethnic groups are excluded from the implementation processes of projects. Livelihood and entrepreneurship opportunities to support adaptation against climate change may be obscured as these entities help to curate positive stories and outcomes rather than emphasize the risks and challenges for future learning outcomes. The GCF seems to act in the best interest of the organization, ensuring no specific implementing entity can exploit positive sentiment towards local inclusion rhetoric to advance their own agenda. As the GCF seems more incentivized to conceal evidence of discriminatory practices in its project implementation, risks and challenges, especially from the beneficiary perspective, tend to be more overlooked. The sources of power international implementing entities wager in the AF, based on their reputations and experience, and the power GCF wages over all implementing entities, based on their robust structure, show how narrative competition can risk exacerbating inequality in climate finance. Insights into power dynamics and stratified relationships drive the need for policy checks in MCFs, as well as further research to understand how local inclusion norm diffusion operates and potentially hampers equitable adaptation and mitigation outcomes in climate finance. Therefore, when assessing local inclusion in climate finance, obtaining the reality of stakeholder engagement may be significantly more arduous than previously thought in the face of robust international implementing entities or MCFs. For the operationalization of future MCFs, such as COP27's Loss and Damage Fund (United Nations Climate Change, 2025), as well as continued operation of existing MCFs these findings show standardized approaches and measurements of local inclusion are required in project implementation to ensure mitigation and adaptation projects are addressing the needs of those most vulnerable to climate change. The measurement of sentiment surrounding local inclusion rhetoric is only the start, serving as an indicator for potential discrimination and ineffectiveness in MCFs.

6.2 Limitations

Despite the feasibility and appropriateness of sentiment analysis and multiple OLS regression, there are still potential limitations that reduce the internal and external validity of this thesis. In terms of case selection, while the GCF and AF are the most appropriate due to their direct-access funding modality, the AF somewhat differs from the GCF, as highlighted in Chapters 3 and 5. The AF has dispersed significantly less funding than the GCF, resulting in fewer projects that can be analyzed. These projects are also adaptation-related, which focuses on building local capacity to climate change and is more favored by beneficiaries, whereas the GCF splits project funding between mitigation, which focuses on carbon emissions reduction, and adaptation financing (Chaudhury, 2020). This discrepancy may create a bias where adaptation-related projects include inherently more positive sentiment of local inclusion than mitigation-funded projects. Further, while the AF documents are predominantly written by external authors, 65% of documents as seen in Figure 23 of the Chapter 5, the GCF documents are written by internal authors, 99% of documents, resulting in a bias towards positive language to improve the image and reputation of these funds, limiting the reliability of the study. Nearly all GCF projects are also ongoing requiring the annual project summary format, whereas completed projects require final evaluation reports. These different types of documents analyzed assess overall progress, risks, and challenges differently, impacting sentiment score surrounding local inclusion rhetoric. While the differences in funding, document type, and timelines may skew the study's results, the inclusion of multiple MCFs across different countries also improves the external validity of this thesis. A larger sample size can not only increase the generalizability and replicability of the study but also improves the accuracy of the multiple OLS regressions performed. The public availability of the documents on the Climate Project Explorer Dataset, as well as the entity specific datasets ensures this study is also replicable.

Regarding sentiment analysis, creating a dictionary for KWIC of local inclusion limits the study's internal validity. Words that match the pre-defined KWIC may be included when not referring to local inclusion such as access used in terms of geographic access. To validate this dictionary, I conferred with external sources, assessing if individuals who manually read a project document selected the same terms related to local inclusion as my model. I also set the window of the KWIC to 30 words before and after the KWIC, which appears generous but may still miss certain phrases that affect average sentiment score. Two documents in the AF corpus, for example, detected no presence of local inclusion rhetoric, decreasing the number of observations available for analysis. Furthermore, sentiment dictionaries cannot accurately detect every observation of positive and negative words, especially with the more formal and technical language most likely adopted in project documents. The Lexicoder dictionary used is also based on negative and positive related words in English, excluding project documents written in Spanish and French. Future studies may consult multiple sentiment dictionaries to improve the internal validity of the results.

The most similar case comparisons outlined in Chapter 5 also encounter limitations. In the most similar case comparison within the AF between the international implementing entity (World Bank) and national direct-access entity (UPCRA), there was significant overlap, yet the World

Bank document was an internally written rather than externally written document. An externally written document would be more useful to analyze to understand the association between external authors and international implementing entities, which was detected in the AF as seen in Figure 20 of Chapter 4. Yet due to the limited number of observations for the AF project documents (49), no other similar case pair was found with an international implementing entity and external author for one project and a national direct-access and internally or externally written other project in the same country. It is also important to note that the project completion document from the World Bank was selected for analysis as the final evaluation report was written in Spanish, further highlighting the limitations of language regarding the English-based sentiment dictionary.

The most similar case comparison between the GCF and AF was also limited by funding allocation contrasts, country characteristics, budget differences, and scale. Despite similar vulnerabilities and adaptive capacities to climate change as well as similar fragile state index scores, the histories of Mauritania and Egypt outline contrasting contexts that are not controlled for in the most similar case comparison. After the 2011 Arab Spring ousting President Hosni Mubarak and ending his 30-year long rule, Abd al-Fattah al-Sisi assumed an authoritarian style of power, silencing opposition and integrating a watchful military presence into civil society (Yefet & Lavie, 2021). In Mauritania, the extent of military rule runs deep, blurring the boundaries between state, civilian, and military structures against the backdrop of a brutal ethno-cultural conflict in which Black Africans are subject to targeted discrimination and state-sponsored violence, despite increasing criticism from civil society (N'Diaye, 2021). These local contexts impact the ability of international implementing entities to execute their projects successfully in cooperation with local governments and executing agencies, potentially impacting project outcomes and sentiment score surrounding local inclusion rhetoric. Further on the project side, the GCF project in Mauritania is ongoing and implemented at a larger scale than the AF project in Egypt (31.8 million USD budget versus 7.8 million USD budget in the AF project). The AF project also reached 78,000 people, while the GCF project is expected to reach 17.2 million people, as seen in Table 11 in Chapter 5. These differences in scale, however, are expected given the contrasting capacities of the GCF and AF discussed earlier. Nonetheless, the limitations of the case studies reduce the internal validity of this thesis. A most-similar case comparison, however, is already limited by its inability to account for equifinality, but this method used to corroborate the OLS multiple regressions still produces valuable insights. As more projects are completed and approved, even more similar cases will be available to draw comparisons between the GCF and AF.

When merging the datasets, the number of observations in the AF and GCF also drops based on the limitations of the controls. In the multiple OLS regression of the AF project documents (Model 1), the number of observations decreases from 55 to 49 as not all countries are included in the Average Civil Society Participation Index, the Average Climate Adaptation (GAINs index), and the Average Fragile State Index. Regarding the GCF, the number of observations included in the regression of Model 2 decreases from 157 to 142. The Average Civil Society Participation Index excludes Antigua and Barbuda, Cook Islands, Samoa, Tuvalu, Dominica, Marshall Islands, and Micronesia. The Average Climate Adaptation Score excludes the Cook Islands and Palestine, and the Average Fragile State Index excludes the Cooks Islands, Tuvalu, Vanuatu, Marshall Islands, and Micronesia.

The entity distribution in the corpus also limits the internal validity of the study. Table 6 in Chapter 3 shows how many of the projects implemented in the GCF are done so by international entities (123) compared to national direct-access (23) and regional direct-access (11), creating more misrepresentation in the study. Regarding the AF, Table 5 in Chapter 3 shows that only one project is implemented by a regional implementing entity, while 24 are implemented by national direct-access entities and 30 by international implementing entities, showing a more even distribution between the two. With only one regional entity present, no relationship can be established between regional implementing entity and sentiment score. The differences in sentiment score between regional and international implementing entities also cannot be accurately measured, accounting for the partial acceptance of H1 and partial rejection of H0 for Model 1. International implementing entities had a more positive sentiment score surrounding local inclusion rhetoric than direct-access entities, but the comparison with regional implementing entities remains inconclusive.

While both funds also have regional implementing entities, in the GCF, this is classified as a regional direct-access entity, yet in the AF, this is just considered a regional entity. While regional entities expect to perceive sentiment surrounding local inclusion rhetoric differently than national direct-access entities as they are more aligned with international implementing entities (Fenton et al., 2014), the different structure of the regional implementing type may have different impacts on sentiment. The difference between these regional entities is controlled with the distinct labeling categories, 2 for regional direct-access and 3 for regional implementing entities, but again the differences remain inconclusive with the limited observations for regional implementing entities in the AF. Due to these limitations, the differences between national direct-access and international implementing entities are more clearly established in this thesis than the differences between regional implementing entities and the other implementing entities. More project observations involving regional implementing entities in the future can help account for this relationship.

Additionally, certain projects were implemented across multiple countries, potentially impacting sentiment score. While all completed projects in the AF were implemented in one country, some GCF projects were implemented at a multi-country level, ranging from two to 42 countries, with the 42-country project being the Global Subnational Climate Fund to offer technical support to stakeholders (Schneck, 2023). Projects with multiple countries resulted in average country scores being calculated for country-specific controls, including the Average Climate Adaptation Score, Average Civil Society Participation Score, and Average Fragile State Index. These averages are most likely less accurate than individual country scores, however, dividing multi-country projects into separate observations risked inflating the multiple OLS regression results, as projects with 19 countries, for example, would be represented by the same project implementation document with the same sentiment score, leading to potential inaccuracies when calculating the coefficients of variables in Model 2. Therefore, while the multi-country project observations may decrease internal validity, splitting these observations risks obscuring the multiple OLS regression results even further.

Another limitation of this thesis relates to the association between international implementing entity type and other variables, including author type, duration, and funding disbursed, measured by project budget. As seen in Figure 20 of Chapter 4, most projects implemented by international entities relied on external authorship for the project documents in Model 1. Chapter 3 also shows international implementing entities in the AF tend to implement longer projects (Figure 5) and manage the largest project budgets in both the GCF and AF, as seen in Figures 7 and 8. The differences in sentiment score could be a result of implementing entity type, as seen partially in Model 1, or may be due to these correlated project characteristics, reducing the internal validity of the study. While these variables are included as controls and removing them could lead to the omitted variable bias, discussed in the multicollinearity tests in

Chapter 4, both models use cross-sectional data limiting the ability to adjust for unobserved heterogeneity, such as additional project-level characteristics, including local institutional relationships or donor involvement, variables not included in the datasets. Future studies using panel data could use fixed-effects regression to better isolate the effect of implementing entity type on sentiment score surrounding local inclusion.

The time constraint of the study also limits the ability to analyze additional explanations of the results. The difference in results between Models 1 and 2 is explained through the different structures of the AF and MCF, with the strength of the structure measured through fiduciary management, financial capacity, technical expertise, and project document structure. Additional differences within the MCFs may also account for the contrasting sentiment score. The structure of the board, who hold final approval power regarding implementing entity accreditation and project proposal approval, is representative in both the AF and GCF of developing and developed countries but operates on different term lengths. The GCF has 24 members serving three-year terms, with no term limit, while the AF has 16 members serving a max of two consecutive two-year terms (Green Climate Fund, 2011; Adaptation Fund, 2018). Understanding how individuals within these structures impact sentiment score could also reveal the norm diffusion capacities or lack thereof in MCFs, where interviews with these board members, as suggested in the future research section, could offer valuable insights. Without the sufficient time or social capital to conduct these interviews, this potential explanation was not explored further. The connection between structure and entity type and sentiment score may also be unique to this thesis's parameters, requiring further testing to corroborate results, as explained in the future research section below.

The limitations of this thesis are summarized in Table 8 below, where each limitation is countered with a mitigation effect to improve overall validity and robustness. While some of these limitations were amended, others, regarding case selection, must be accepted as limitations that can reduce the internal and external validity of the results.

Table 12: Limitations Table

Limitation	Potential Validity Threat	Mitigation Used
1. Different structures of the AF and GCF	External validity: limits generalizability between MCFs	Inclusion of multiple MCFs also improves external validity
2. Different number of observations for AF and GCF	External validity: fewer cases reduce generalizability	Unable to mitigate until more observations are available in the future
3. Different document types between AF and GCF (annual vs. final evaluation reports)	Internal validity: different structure affects comparability	Not directly controlled for but assessed and discussed in analysis with most similar case comparisons
4. Multi-country project observations in the GCF	Internal validity: averaging scores can weaken measurement accuracy	Controlled with average scores; splitting projects would artificially inflate sample
5. Reduced observations with country controls	External validity: fewer cases reduce generalizability	Multiple measures to control for country stability and institutional capacity still improve internal validity
6. Projects in AF and GCF have different statuses (completed vs. ongoing)	Internal validity: different structure affects comparability	Not directly controlled for but assessed and discussed in analysis with most similar case comparisons
7. Limited regional implementing entities	Internal validity: less observations reduces generalizability	Unable to mitigate until more observations are available in the future
8. Different authorship of documents between funds (internal vs external)	Internal validity: different structure affects comparability	Included as a control (author type) in the OLS multiple regressions
9. KWIC local inclusion dictionary limited by definition and word window	Internal validity: misclassify or miss local inclusion terms	Validated with manual review and complemented by quotes analyzed in the most similar case comparisons
10. Language exclusion with sentiment analysis	Internal validity: fewer cases reduce generalizability	Future research may include multilingual sentiment dictionaries

11. Differences in cases selected for most similar case comparison	Internal validity: more difficult to isolate differences	Unable to mitigate until more observations are available in the future
12. Correlation between implementing entity type and project characteristics	Internal validity: risks of multicollinearity	Controlled for with multicollinearity tests in Chapter 4
13. Use of cross-sectional data	Internal validity: cannot account for unobserved heterogeneity	Future research using panel data could test with fixed-effects model
14. Time constraint of thesis	Internal validity: limited time for methodology triangulation	Unable to mitigate

6.3 Future Research

As this thesis novelly contributes to climate finance and climate justice fields with a quantitative measurement of sentiment surrounding local inclusion rhetoric in MCF project implementation, future research can expand on these findings with complementary methodology, additional observations, and additional cases. Future studies can confirm or disprove the norm diffusion pathways found in this thesis, perhaps showing there is no relationship between fund structure and implementing entities' ability to diffuse local inclusion norms. A study measuring the sentiment surrounding local inclusion as expressed by beneficiaries would provide further insights into how implementing entities impact the perception of local inclusion and stakeholder engagement. Relying on interviews and surveys allows for a deep dive exploration of projects to better assess underlying power dynamics and norms that may mask further marginalization or challenges. Interviewing GCF and AF secretariat and board members, as well as officials of implementing entities, would also help explore the driving factors of norm diffusion and how these norms are observed and interpreted. Performing this study again after the GCF has completed more projects can also help uncover if the GCF diffuses local inclusion norms in the final evaluation stage of projects rather than just in the annual project summary documents. Additional observations can also improve the representativeness of different implementing entity types, strengthening the robustness of the multiple OLS regressions. More observations will show if statistical relationships found in Models 1 and 2 for the projects per entity variable and Model 2 for the duration variable hold as well, determining whether further investigation is required to explain the results. A study investigating other MCFs, such as the Global Environment Facility, could also assess if and how local inclusion norms are diffused when only international and regional implementing entities execute projects. As MCFs increasingly mobilize more finance for adaptation and mitigation, academics must maintain a similar pace with their analyses, ensuring local inclusion translates to effective and equitable climate finance for a sustainable future.

References

Abnett, K., Volcovici, V., & Strohecker, K. (2024, November 24). Developing nations blast $300 billion COP29 climate deal as insufficient. *Reuters.* https://www.reuters.com/sustainability/sustainable-finance-reporting/wealthy-countries-back-raising-cop29-climate-deal-300-billion-sources-say-2024-11-23/

Achamkulangare, G. (2021). *Review of the management of implementing partners in United Nations system organizations JIU/REP/2021/4.* United Nations Joint Inspection Unit. https://documents.un.org/doc/undoc/gen/g22/261/08/pdf/g2226108.pdf

Adaptation Fund. (2018). *Rules of procedure of the Adaptation Fund Board.* https://www.adaptation-fund.org/wp-content/uploads/2018/04/Rules-of-procedure-of-the-Adaptation-Fund-Board.pdf

Adaptation Fund. (2019). *Annex I: Amendment of the terms and conditions of trustee services to be provided by the World Bank as an interim trustee of the fund.* https://www.adaptation-fund.org/wp-content/uploads/2022/08/TC_amended-in-Nov-2019.pdf

Adaptation Fund. (2020a). *Climate adaptation finance: Direct-access*. https://www.adaptation-fund.org/wp-content/uploads/2019/11/Direct-Access-June-2020.pdf

Adaptation Fund. (2020b*). Local leadership in adaptation finance: Learning from locally-led action in Adaptation Fund projects and programmes*. https://www.adaptation-fund.org/wp-content/uploads/2020/09/Local-Leadership-in-Adaptation-Finance-publication-1.pdf

Adaptation Fund. (2022). *Operational policies and guidelines for parties to access resources from the adaptation fund (OPG).* https://www.adaptation-fund.org/wp-content/uploads/2017/08/Amended-OPG_Oct-2022_2.pdf

Adaptation Fund. (2024a). *About.* https://www.adaptation-fund.org/about/

Adaptation Fund. (2024b) *Alternative and Private Sector Sources.* https://www.adaptation-fund.org/about/resource-mobilization/alternative-and-private-sector-sources/

Adaptation Fund. (2024c). Complaint handling mechanisms of implementing entities. https://www.adaptation-fund.org/projects-programmes/accountability-complaints/complaint-handling-mechanisms-implementing-entities/

Adaptation Fund. (2024d). *Project table view.* https://www.adaptation-fund.org/projects-programmes/project-information/projects-table-view/

Adaptation Fund. (2024e). Secretariat. https://www.adaptation-fund.org/about/governance/secretariat/

Adaptation Fund. (2025a). *Implementing entities.* https://www.adaptation-fund.org/apply-funding/implementing-entities/

Adaptation Fund. (2025b) *Readiness grants.* https://www.adaptation-fund.org/readiness/readiness-grants.

Afaneh, A. (2024). *Annual performance report CY2023: FP053 enhancing climate change adaptation in the North coast and Nile Delta regions in Egypt.* Green Climate Fund. https://www.greenclimate.fund/sites/default/files/document/fp053-annual-performance-report-cy2023.pdf

Alcañiz, I., & Giraudy, A. (2023). From international organizations to local governments: how foreign environmental aid reaches subnational beneficiaries in Argentina, Brazil, and Mexico. *Environmental Politics, 32*(4), 663-683. https://doi.org/10.1080/09644016.2022.2124004

Avila, P. (2019). *Final evaluation: Project Family agriculture adaptation and resilience in Northeast Argentina to climate change and variability impacts.* Adaptation Fund. https://cdn.climatepolicyradar.org/navigator/ARG/2013/enhancing-the-adaptive-capacity-and-increasing-resilience-of-small-size-agriculture-producers-of-the-northeast-of-argentina_833dfa88dfb20b479496d873ab4f36e5.pdf

Babb, S., & Kentikelenis, A. (2018). International financial institutions as agents of neoliberalism. In D. Cahill, M. Cooper, M. Konings, & D. Primrose (Eds.), *The SAGE* *handbook of neoliberalism* (pp.16-27). Sage Publications. https://doi.org/10.4135/9781526416001.n3

Basak, R., & Karlsson-Vinkhuyzen, S. (2022). Chapter 6: The Green Climate Fund: History, status and legitimacy. In A. Michaelowa & A.K. Sacherer (Eds.), *Handbook of international climate finance* (pp. 135-166). Edward Elgar Publishing. https://doi.org/10.4337/9781784715656.00013

Basak, R., & van der Werf, E. (2019). Accountability mechanisms in international climate change financing. *International Environmental Agreements: Politics, Law and Economics, 19*(3), 297–313. https://doi.org/10.1007/s10784-019-09437-8

Bartsiotas, G., & Prom-Jackson, S. (2013). *Review of the management of implementing partners in United Nations system organizations JIU/REP/2013/4.* United Nations Joint Inspection Unit. https://www.unjiu.org/sites/www.unjiu.org/files/jiu_document_files/products/en/reports-notes/JIU%20Products/JIU_REP_2013_4_English.pdf

Bennet, A. (2004). Case study methods: Design, use, and comparative advantages. In D. Sprinz & Y. Wolinksy-Nahmias (Eds.), *Models, numbers, and cases: Methods for studying international relations*, (pp. 19-55). University of Michigan Press.https://lib.ugent.be/catalog/rug01:001047496

Bertilsson, J., & Soneryd, L. (2023). Indigenous peoples and inclusion in the green climate fund. *Environmental Sociology*, *9*(3), 233–242. https://doi.org/10.1080/23251042.2023.2177091

Bertilsson, J., & Thörn, H. (2021). Discourses on transformational change and paradigm shift in the Green Climate Fund: The divide over financialization and country ownership. *Environmental Politics, 30*(3), 423–441. https://doi.org/10.1080/09644016.2020.177544

Betzold, C., & Weiler, F. (2017). Allocation of aid for adaptation to climate change: Do vulnerable countries receive more support? *International Environmental Agreements: Politics, Law and Economics*, *17*(1), 17–36. https://doi.org/10.1007/s10784-016-9343-8

Bhandary, R. R., Gallagher, K.S., & Zhang, F. (2021). Climate finance policy in practice: a review of the evidence. *Climate Policy, 21*(4), 529-545. https://doi.org/10.1080/14693062.2020.1871313

Bird, G. (1994). Changing partners: Perspectives and policies of the Bretton Woods institutions. *Third World Quarterly*, *15*(3), 483–503. https://www.jstor.org/stable/3993296

Bracking, S., & Leffel, B. (2021). Climate finance governance: Fit for purpose? *Wiley Interdisciplinary Reviews: Climate Change*, *12*(1), 1-18. https://doi.org/10.1002/wcc.709

Breusch, T. S., & Pagan, A. R. (1979). A simple test for heteroskedasticity and random coefficient variation. *Econometrica*, *47*(5), 1287–1294. https://doi.org/10.2307/1911963.

Browne, K. E. (2022). Rethinking governance in international climate finance: Structural change and alternative approaches. *WIREs Climate Change*, *13*(5), 1-23. https://doi.org/10.1002/wcc.795

Caldwell, M., & Larsen, G. (2021). *INSIDER: Three ways to improve direct-access to the Green Climate Fund.* World Resources Institute. https://www.wri.org/technical-perspectives /insider-three-ways-improve-direct-access-green-climate-fund

Chan, C., Bajjalieh, J., Auvil, L., Wessler, H., Althaus, S., Welbers, K., van Atteveldt, W., & Jungblut, M. (2021). Four best practices for measuring news sentiment using 'off-the-shelf' dictionaries: a large-scale p-hacking experiment. *Computational Communication Research, 3*(1), 1-27. https://doi.org/10.5117/CCR2021.1.001.CHAN

Chaudhury, A. (2020). Role of intermediaries in shaping climate finance in developing countries—lessons from the Green Climate Fund. *Sustainability*, *12*(14), 1-17. https://doi.org/10.3390/su12145507

Chu, E., Anguelovski, I., & Carmin, J. (2016). Inclusive approaches to urban climate adaptation planning and implementation in the Global South. *Climate Policy*, *16*(3), 372–392. https://doi.org/10.1080/14693062.2015.1019822

Ciplet, D., Falzon, D., Uri, I., Robinson, S., Weikmans, R., & Roberts, J. T. (2022). The unequal geographies of climate finance: Climate injustice and dependency in the world system. *Political Geography*, *99*(1), 1-12. https://doi.org/10.1016/j.polgeo.2022.102769

Clean Investment Fund. (2025). *CIF Funding.* https://www.cif.org/cif-funding

Climate Project Explorer. (2025). *Multilateral climate funds*. Climate Policy Radar. https://climateprojectexplorer.org/search

Colenbrander, S., Dodman, D., & Mitlin, D. (2018). Using climate finance to advance climate justice: The politics and practice of channeling resources to the local level. *Climate Policy*, *18*(7), 902-915. https://doi.org/10.1080/14693062.2017.1388212

Diamond, L. (2024). Power, performance, and legitimacy. *Journal of Democracy, 35*(2), 5-22. https://doi.org/10.1353/jod.2024.a922830

Doshi, D., & Garschagen, M. (2020). Understanding adaptation finance allocation: Which factors enable or constrain vulnerable countries to access funding? *Sustainability*, *12*(10), 1-18. https://doi.org/10.3390/su12104308

Dougherty, C. (2011). *Introduction to Econometrics (4th Edition).* Oxford University Press.

Fenton, A., Gallagher, D., Wright, H., Huq, S., & Nyandiga, C. (2014). Up-scaling finance for community-based adaptation. *Climate and Development*, *6*(4), 388–397. https://doi.org/10.1080/17565529.2014.953902

Finnemore, M., & Sikkink, K. (1998). International norm dynamics and political change. *International Organization*, *52*(4), 887–918. https://doi-org.ezproxy.leidenuniv.nl/10.1162/002081898550789

Fox, J., & Monette, G. (1992). Generalized collinearity diagnostics. *Journal of the American Statistical Association*, *87*(417), 178–183. https://doi.org/10.1080/01621459.1992.10475190

Fund for Peace. (2023). *Fragile states index.* https://fragilestatesindex.org/excel/

Gallagher, K. P., Bhandary, R. R., Ray, R., & Ramos, L. (2023). Reforming Bretton Woods institutions to achieve climate change and development goals. *One Earth*, *6*(10), 1291–1303. https://doi.org/10.1016/j.oneear.2023.09.009

Gehring, T., & Vizitiu, P. (2024). Organizational autonomy beyond the secretariat: Lessons from the Green Climate Fund. *Global Environmental Politics, 24*(4), 83–104. https://doi.org/10.1162/glep_a_00764

Georgeson, L., & Maslin, M. (2018). Putting the United Nations Sustainable Development Goals into practice: A review of implementation, monitoring, and finance. *Geo: Geography and Environment*, *5*(1), 1-25. https://doi.org/10.1002/geo2.49

Global Environment Facility. (2025). *Projects.* https://www.thegef.org/projects-operations/database

Graham, E. R., & Serdaru, A. (2020). Power, control, and the logic of substitution in institutional design: The case of international climate finance. *International Organization*, *74*(4), 671–706. https://doi.org/10.1017/S0020818320000181

Green Climate Fund. (2011). *Governing instrument.* https://www.greenclimate.fund/document/governing-instrument

Green Climate Fund. (2019). *GCF in brief: Enhancing direct-access.* https://www.greenclimate.fund/document/gcf-brief-enhancing-direct-access

Green Climate Fund. (2024a). *About us partners: NDAS.* https://www.greenclimate.fund/about/partners/nda.

Green Climate Fund. (2024b). *About us partners: Accredited entities.* https://www.greenclimate.fund/about/partners/ae

Green Climate Fund. (2024c). *Open data library.* https://data.greenclimate.fund/public

Green Climate Fund. (2025a). *Entity accreditation* https://www.greenclimate.fund/accreditation/process

Green Climate Fund. (2025b). *Project portfolio.* https://www.greenclimate.fund/projects?f[]=field_status:445

Green Climate Fund. (2025c). *Secretariat*. https://www.greenclimate.fund/about/secretariat

Global Environment Facility. (2025). *GEF agencies.* https://www.thegef.org/partners/gef-agencies

Herre, B., Rodés-Guirao, L., & Ortiz-Ospina, E. (2023). *Civil society participation index.* Our World in Data. https://ourworldindata.org/grapher/civil-society-participation-index

Independent Evaluation Unit. (2023). *Independent synthesis of direct-access in the Green Climate Fund.* Evaluation report No. 15. Songdo, South Korea: Independent Evaluation Unit, Green Climate Fund. https://ieu.greenclimate.fund/document/final-report-independent-synthesis-direct-access-green-climate-fund

Independent Redress Mechanism. (2025). *Case register.* https://irm.greenclimate.fund/case-register

Islam, M. (2022). Distributive justice in global climate finance – Recipients' climate vulnerability and the allocation of climate funds. *Global Environmental Change*, *73*(1), 1-15. https://doi.org/10.1016/j.gloenvcha.2022.102475

Jasleen, K. & Saini, J.R. (2024). Emotion detection and sentiment analysis in text corpus: A differential study with informal and formal writing styles. *International Journal of Computer Application, 101*(9), 1-9. https://ssrn.com/abstract=3291299

Jacobs, M. (2024, June 21). *The new development and climate finance agenda*. ODI Global. https://odi.org/en/insights/the-new-development-and-climate-finance-agenda/

Kalinowski, T. (2024). The Green Climate Fund and private sector climate finance in the Global South. *Climate Policy*, *24*(3), 281–296. https://doi.org/10.1080/14693062.2023.2276857

Kuhl, L., & Shinn, J. (2022). Transformational adaptation and country ownership: Competing priorities in international adaptation finance. *Climate Policy*, *22*(9–10), 1290–1305. https://doi.org/10.1080/14693062.2022.2104791

Liang, C., & Liu, B. (2020). Challenge or opportunity of climate financial fragmentation: Evidence from China-initiated cooperation with emerging multilateral institutions. *International Journal of Climate Change Strategies and Management*, *12*(3), 289–303. https://doi.org/10.1108/IJCCSM-07-2019-0048

Mathur-Filipp, J., & Bista, P. (2015). *NIE accreditation Toolkit.* Adaptation Fund. https://www.adaptation-fund.org/wp-content/uploads/2015/07/Accreditation-Toolkit-English-14.pdf

Mansuri, G., & Rao, V. (2013). *Localizing development: Does participation work?* World Bank. https://openknowledge.worldbank.org/server/api/core/bitstreams/dbf44593-5927-5acc-b1a2-3e1870600713/content

Möller, B. (2019). From exclusion to inclusion: The understanding, capacity, and will to change local government practices. In B. Dahiya & A. Das (Eds.), *New Urban Agenda in Asia-Pacific* (pp. 331–350). Springer. https://doi.org/10.1007/978-981-13-6709-0_12

Moreyra, A., Pietragalla, V., & Bernardini, T. (2020). *Project completion summary: TF 015041 increasing climate resilience and enhancing sustainable land management in the Southwest of the Buenos Aires province*. Adaptation Fund. https://cdn.climatepolicyradar.org/navigator/ARG/2012/increasing-climate-resilience-and-enhancing-sustainable-land-management-in-the-southwest-of-the-buenos-aires-province_a0ce41bdd1fd1180814e3afd66e43230.pdf

Müller, B., & Bhandary, R. R. (2022). Chapter 14: Enhanced direct-access: The first decade. In A. Michaelowa & A.K. Sacherer (Eds.), *Handbook of international climate finance* (pp. 333-351). Edward Elgar Publishing. https://doi.org/10.4337/9781784715656.00022

N'Diaye, B. (2021). Mauritania: Exceptionalism and vulnerability. In L. Villalón (Ed.), The Oxford Handbook of the African Sahel, (pp.109-126). Oxford Academic. https://doi-org.ezproxy.leidenuniv.nl/10.1093/oxfordhb/9780198816959.013.3

Nilsson, A. (2017). Making norms to tackle global challenges: The role of ntergovernmental Organisations. *Research Policy*, *46*(1), 171–181. https://doi.org/10.1016/j.respol.2016.09.012

Notre Dame Global Adaptation Initiative Country Index (ND-GAIN). (2024). Indicators. *University of Notre Dame.* https://gain.nd.edu/our-work/country-index/download-data/

Ogunyiola, A., Gardezi, M., & Vij, S. (2022). Smallholder farmers' engagement with climate smart agriculture in Africa: Role of local knowledge and upscaling. *Climate Policy*, *22*(4), 411–426. https://doi.org/10.1080/14693062.2021.2023451

Omukuti, J. (2020). Country ownership of adaptation: Stakeholder influence or government control? *Geoforum*, *113*, 26–38. https://doi.org/10.1016/j.geoforum.2020.04.019

Omukuti, J., Barrett, S., White, P. C. L., Marchant, R., & Averchenkova, A. (2022). The green climate fund and its shortcomings in local delivery of adaptation finance. *Climate Policy, 22*(9–10), 1225–1240. https://doi.org/10.1080/14693062.2022.2093152

Park, S. (2005). Norm diffusion within international organizations: A case study of the World Bank. *Journal of International Relations and Development*, *8*(2), 111–141. https://doi.org/10.1057/palgrave.jird.1800051

Park, S. (2006). Theorizing norm diffusion within international organizations. *International Politics*, *43*(3), 342–361. https://doi.org/10.1057/palgrave.ip.8800149

Price, R. (2021). *Access to climate finance by women and marginalized groups in the Global South*. The Institute of Development Studies and Partner Organizations. https://doi.org/10.19088/K4D.2021.083']

Saadani, Y., & Selmane, M. (2019). *Final project evaluation: Project for enhancing community resilience and food security to adverse effects of climate change in Mauritania.*

Adaptation Fund. https://cdn.climatepolicyradar.org/navigator/MRT/2012/enhancing-resilience-of-communities-to-the-adverse-effects-of-climate-change-on-food-security-in-mauritania_74402cb798f6cd1a706db18d02d45899.pdf

Saunders, N. (2019). *Climate change adaptation finance: are the most vulnerable nations prioritised?* Stockholm Environment Institute. https://www.sei.org/publications/climate-adaptation-finance-vulnerable-nations/

Schneck, J. (2023). *Global Subnational Climate Fund (SnCF Global) – Technical assistance (TA) Facility: Annual performance report.* Green Climate Fund. https://www.greenclimate.fund/sites/default/files/document/fp151-annual-performance-report-cy2023.pdf

Simmons, B., & Martin, L. (2012). International organisations and institutions. In W. Carlsnaes, T. Risse, & B. Simmons (Eds.), *Handbook of International Relations* (pp. 326–351). Sage Publications. ISBN 978-1849201506

Skovgaard, J., Adams, K. M., Dupuy, K., Dzebo, A., Funder, M., Fejerskov, A. M., & Shawoo, Z. (2023). Multilateral climate finance coordination: Politics and depoliticization in practice. *Global Environmental Politics*, *23*(2), 125–147. https://doi.org/10.1162/glep_a_00703

United Nations Economic and Social Council. (1997). *Report of the Economic and Social Council for 1997 A/52/3.18*. https://digitallibrary.un.org/record/271316?v=pdf

United Nations Environment Program. (2022). *Adaptation gap report 2022: Too little, too slow – Climate adaptation failure puts world at risk — Online annexes.* https://www.unep.org/adaptation-gap-report-2022

United Nations Environment Program. (2023). *Adaptation gap report 2023: Underfinanced. Underprepared. Inadequate investment and planning on climate adaptation leaves world exposed- Online annexes*. https://www.unep.org/resources/adaptation-gap-report-2023

United Nations Climate Change. (2025). *Fund for responding to Loss and Damage*. https://unfccc.int/loss-and-damage-fund-joint-interim-secretariat

Weiler, F., Klöck, C., & Dornan, M. (2018). Vulnerability, good governance, or donor interests? The allocation of aid for climate change adaptation. *World Development*, *104*(1), 65–77. https://doi.org/10.1016/j.worlddev.2017.11.001

Yefet, B., & Lavie, L. (2021). Legitimation in post-revolutionary Egypt: Al-Sisi and the renewal of authoritarianism. *Digest of Middle East Studies, 30*(3), 170–185. https://doi-org.ezproxy.leidenuniv.nl/10.1111/dome.12244

Young, L. & Soroka, S. (2012). *Lexicoder sentiment dictionary*. http://lexicoder.com

Zetterli, P., Larsen, G., & Davey, E. (2025). *Inclusive finance can deliver climate funding into the hands of people who need it most*. World Resource Institute. https://www.wri.org/insights/inclusive-climate-finance

Appendix

```
#Thesis Code Sarah Stuttaford
#install.packages("tesseract")
#install.packages("magick")
#install.packages("sf")
#install.packages("rnaturalearth")
#install.packages("rnaturalearthdata")
#install.packages("car")
#install.packages("lmtest")
#install.packages("sjPlot")
library(sjPlot)
library(tesseract)
library(magick)
library(tidyverse)
library(ggplot2)
library(dplyr)
library(rio)
library(httr)
library(pdftools)
library(quanteda)
library(readtext)
library(tm)
library(data.table)
library(future.apply)
library(sf)
library(rnaturalearth)
library(rnaturalearthdata)
library(countrycode)
library(reshape2)
library(kableExtra)
library(car)
library(lmtest)
library(stargazer)

#STEP 1 download datasets
Project_documents <- import("AF_GCF_project_documents_2025_23_2_v2.csv")

#filtering duplicated colnames
Project_documents_filtered <- Project_documents %>%
  select(-which(duplicated(colnames(Project_documents))))
```

```
#english only text
Project_documents_filtered <- Project_documents_filtered %>%
  filter(Languages == "English")

#Only AF documents
Project_AF <- Project_documents_filtered %>%
  filter(Source == "AF")

#Add Adaptation Fund entity data, check matching carefully
AF_entity_projects <- import("adaptation-fund-february 17th 2025.csv")
AF_info <- Project_AF %>%
  left_join(AF_entity_projects, by = c("Family Name" = "projecttitle", "Implementing_Agency"
= "ie", "Geographies" = "country_code"))

#filter for completed projects in status
AF_info_0 <- AF_info %>%
  filter(status == "Project Completed")

#only final evaluation and project completion in document title
AF_info_1_ <- AF_info_0 %>%
  filter(`Document Title` == "Final evaluation report" |`Document Title` == "Project completion
report" | `Document Title` == "completion report")

#still project duplicates so need to continue filtering by removing author blanks
AF_info_1 <- AF_info_1_ %>%
  filter(`author` != "" & !is.na(`author`))

#STEP 2 ADD CONTROLS
#match with average civil society score from 2010-2023 per country
civil_society_index <- import("civil-society-participation-index.csv", sheet="Sheet2")
civil_society_score <- civil_society_index %>%
  select(Country, `Average 2010-2023 index`)
civil_society_score <- civil_society_score %>%
  rename(avg_civil_score = `Average 2010-2023 index`)

#match based on country code for accuracy
world <- ne_countries(scale = "medium", returnclass = "sf")
world_data <- world %>%
  left_join(civil_society_score, by = c("name" = "Country"))
```

```
#match countries correctly using country_code package
civil_society_score$iso3 <- countrycode(civil_society_score$Country, "country.name", "iso3c")

AF_info_IVs <- AF_info_1 %>%
  left_join(civil_society_score, by = c("Geographies" = "iso3"))

#add climate adaptation (gains index)
gains_index <-import("gain_2015_2022.csv")
gains_index <- gains_index %>%
  select(Name, `average_gain_2010-2022`)
gains_index <- gains_index %>%
  rename(avg_climate_adaptation_score =`average_gain_2010-2022`)

gains_index$iso3 <- countrycode(gains_index$Name, "country.name", "iso3c")

AF_info_IVs_0 <- AF_info_IVs %>%
  left_join(gains_index, by = c("Geographies" = "iso3"))

#add fragile state index score
FS_index <- import("FCS index.xlsx", sheet="Sheet14")
FSI <- FS_index %>%
  select(Country, `FCS Average 2010-2023`)
FSI <- FSI %>%
  rename(avg_fsi_score =`FCS Average 2010-2023`)
FSI$iso3 <- countrycode(FSI$Country, "country.name", "iso3c")

AF_info_IVs <- AF_info_IVs_0 %>%
  left_join(FSI, by = c("Geographies" = "iso3"))

#STEP 3 DESCRIPTIVE STATISTICS
#create doughnut chart to see implementing entity type distribution of AF in completed projects
#summarize entity types and change labeling
entity_counts <- AF_info_IVs %>%
  select(Implementing_Agency, ietype) %>%
  distinct() %>%  # ensures unique (Implementing_Agency, ietype) pairs
  mutate(
    International = str_detect(ietype, "MIE"),
    National_DAE = str_detect(ietype, "NIE"),
    Regional = str_detect(ietype, "RIE")
```

```
  ) %>%
  summarise(
    International = sum(International),
    National_DAE = sum(National_DAE),
    Regional = sum(Regional)
  ) %>%
  pivot_longer(everything(), names_to = "EntityType", values_to = "Count")

#create percentage for doughnut chart
entity_counts <- entity_counts %>%
  mutate(
    percent = Count / sum(Count),
    label = paste0(round(percent * 100), "%")
  )
#create doughnut chart
ggplot(entity_counts, aes(x = 2, y = Count, fill = EntityType)) +
  geom_bar(stat = "identity", width = 1, color = "white") +
  coord_polar(theta = "y") +
  xlim(0.5, 2.8) +
  geom_text(aes(x = 2.75, label = label),  # bump x outwards
            position = position_stack(vjust = 0.5),
            size = 4, color = "black") +
  theme_void() +
  scale_fill_manual(values = c(
    "National_DAE" = "#388E3C",  # blue
    "Regional" = "#8BC34A",  # orange
    "International"  = "#FFE082"   # green
  )) +
  theme(legend.position = "right") +
  ggtitle("Adaptation Fund") +
  theme(plot.title = element_text(hjust = 0.5))

#Project funding disbursed per completed project
#summarize based on implementing entity type
AF_info_IVs <- AF_info_IVs %>%
  mutate(ietype1 = ifelse(ietype == "NIE", "National_DAE",
                   ifelse(ietype == "RIE", "Regional",
                          ifelse(ietype == "MIE", "International", NA))))

AF_info_IVs$amount_disbursed <- as.numeric(gsub(",", "", AF_info_IVs$amount_disbursed))
```

```
funding_by_ie <- AF_info_IVs %>%
  group_by(Implementing_Agency, ietype1) %>%
  summarise(total_disbursed = sum(amount_disbursed, na.rm = TRUE), .groups = "drop")

#visualize with names of entities to see which entities receive the most funding in a bar chart
ggplot(funding_by_ie, aes(x = reorder(Implementing_Agency, -total_disbursed), y =
total_disbursed, fill = ietype1)) +
  geom_bar(stat = "identity") +
  labs(
    title = "AF: Total Funding Disbursed by Implementing Entity",
    x = "Implementing Entity",
    y = "Total Disbursed Amount (USD)"
  ) +
  theme_minimal() +
  scale_fill_manual(values = c(
    "National_DAE" = "#388E3C",  # blue
    "Regional" = "#8BC34A",  # orange
    "International"  = "#FFE082"   # green
  )) +
  coord_flip() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

#summarize funding based on entity type
funding_by_ie2 <- AF_info_IVs %>%
  group_by(ietype1) %>%
  summarise(total_disbursed = sum(amount_disbursed, na.rm = TRUE), .groups = "drop")

#get percent
funding_by_ie2 <- funding_by_ie2 %>%
  mutate(
    percent = total_disbursed / sum(total_disbursed),
    label = paste0(round(percent * 100), "%")
  )
ggplot(funding_by_ie2, aes(x = 2, y = total_disbursed, fill = ietype1)) +
  geom_bar(stat = "identity", width = 1, color = "white") +
  coord_polar(theta = "y") +
  xlim(0.5, 2.8) +
  geom_text(aes(x = 2.75, label = label),  # bump x outwards
           position = position_stack(vjust = 0.5),
           size = 4, color = "black") +
```

```
  theme_void() +
  scale_fill_manual(values = c(
    "National_DAE" = "#388E3C",
    "Regional" = "#8BC34A",
    "International"  = "#FFE082"
  )) +
  theme(legend.position = "right") +
  ggtitle("Adaptation Fund") +
  theme(plot.title = element_text(hjust = 0.5))

#author type of project documents
#count author type
author_type <- AF_info_IVs %>%
  select(author) %>%
  mutate(
    External = str_detect(author, "External"),
    Internal = str_detect(author, "Internal")
  ) %>%
  summarise(
    External = sum(External),
    Internal = sum(Internal)
  ) %>%
  pivot_longer(everything(), names_to = "Authortype", values_to = "Count")
"C:/Users/Sarah/Desktop/thesis/Descriptive stats images/AF total funding disbursed by
implementing entity.png"
#create doughnut chart to visualize
author_type1 <- author_type %>%
  mutate(
    percent = Count / sum(Count),
    label = paste0(round(percent * 100), "%")
  )

#relationship between implementing entity type and author
author_counts_by_ie_type <- AF_info_IVs %>%
  mutate(
    author_trimmed = trimws(author),
    # Recode 'author' into a numeric type: 0 for Internal, 1 for External
    author_type = ifelse(author_trimmed == "Internal", 0,
                      ifelse(author_trimmed == "External", 1, NA))
  ) %>%
```

```
  filter(!is.na(author_type)) %>% # Remove rows where author_type couldn't be determined
  group_by(ietype1, author_type) %>%
  summarise(project_count = n(), .groups = 'drop') # Count projects for each combination

#plotting filtered df
ggplot(author_counts_by_ie_type, aes(x = ietype1, y = project_count, fill = factor(author_type)))
+
  geom_bar(stat = "identity") +
  scale_fill_manual(values = c("0" = "lightblue", "1" = "darkblue"), # 0: Internal (lightblue), 1:
External (darkblue)
                    labels = c("0" = "Internal Author", "1" = "External Author")) +
  labs(
    title = "AF: Author Type per Project",
    x = "Implementing Entity",
    y = "Number of Projects Implemented",
    fill = "Author Type" # Legend title
  ) +
  theme_minimal() +
  coord_flip() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

#Project duration visual
#change duration in years to numeric
AF_info_IVs$duration <- as.numeric(gsub(" years", "", AF_info_IVs$duration))

#subset
duration_AF <- AF_info_IVs %>%
  select(duration, ietype1, Project_Id) %>%
  distinct()

#average duration per implementing entity type
avg_durationAF <- duration_AF %>%
  group_by(ietype1) %>%
  summarise(avg_duration = mean(duration, na.rm = TRUE))

#visualize in bar chart
ggplot(avg_durationAF, aes(x = ietype1, y = avg_duration, fill = ietype1)) +
  geom_bar(stat = "identity") +
  labs(
    title = "AF: Average Completed Project Duration by Entity Type",
```

```
    x = "Completed Project",
    y = "Time (years)"
  ) +
  theme_minimal() +
  scale_fill_manual(values = c(
    "National_DAE" = "#388E3C",
    "Regional" = "#8BC34A",
    "International"  = "#FFE082"
  )) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

#to get the mean and median
summary(AF_info_IVs$duration)
#Visualize civil society index by matching average country score with world map

world_data <- world %>%
  left_join(civil_society_score, by = c("iso_a3_eh" = "iso3"))

#create world map with color gradient to indicate score
ggplot(world_data) +
  geom_sf(aes(fill = avg_civil_score), color = "white", size = 0.2) +
  scale_fill_gradient(
    name = "Average Civil Society Index",
    low = "#D73027",  # pale yellow
    high = "#1A9850", # dark green
    na.value = "gray90"  # for countries without data
  ) +
  theme_minimal() +
  labs(title = "Average Civil Society Index (2010–2023)") +
  theme(
    legend.position = "right",
    plot.title = element_text(hjust = 0.5)
  )

#Climate adaptation index (gains index)
#repeat same steps as with civil society index which means adding country codes and joining it to the world dataset
gains_index$iso3 <- countrycode(gains_index$Name, "country.name", "iso3c")

# Join using ISO codes
```

```
world_data <- world %>%
  left_join(gains_index, by = c("iso_a3_eh" = "iso3"))

#visualize with world map
ggplot(world_data) +
  geom_sf(aes(fill = avg_climate_adaptation_score), color = "white", size = 0.2) +
  scale_fill_gradient(
    name = "Average GAINS Score",
    low = "#D73027",  # pale yellow
    high = "#1A9850", # dark green
    na.value = "gray90"  # for countries without data
  ) +
  theme_minimal() +
  labs(title = "Average Climate Adaptation Score (2010–2023)") +
  theme(
    legend.position = "right",
    plot.title = element_text(hjust = 0.5)
  )

#Fragile state index
#repeat same steps as with gains score which means adding country codes and joining it to the world dataset
FSI$iso3 <- countrycode(FSI$Country, "country.name", "iso3c")
# Join using ISO codes
world_data <- world %>%
  left_join(FSI, by = c("iso_a3_eh" = "iso3"))

#FSI
ggplot(world_data) +
  geom_sf(aes(fill = avg_fsi_score), color = "white", size = 0.2) +
  scale_fill_gradient(
    name = "Average Fragile State Score",
    low = "#1A9850",  # pale yellow
    high = "#D73027", # dark green
    na.value = "gray90"  # for countries without data
  ) +
  theme_minimal() +
  labs(title = "Average Fragile State Score (2010–2023)") +
  theme(
    legend.position = "right",
```

```
    plot.title = element_text(hjust = 0.5)
  )

#projects per country
#After filtering for AF, each project only contains one country country per project

#darker gradient shows more projects going on in a country
project_counts <- AF_info_IVs %>%
  count(Geographies, name = "Project_Count")

world_data <- world %>%
  left_join(project_counts, by = c("iso_a3_eh" = "Geographies"))

ggplot(world_data) +
  geom_sf(aes(fill = Project_Count), color = "white", size = 0.2) +
  scale_fill_gradient(
    name = "Number of Projects",
    low = "lightgreen",    # light green
    high = "darkgreen",   # dark green
    na.value = "grey90" # for countries with no data
  ) +
  theme_minimal() +
  labs(title = "AF Completed Project Geographic Distribution") +
  theme(
    legend.position = "right",
    plot.title = element_text(hjust = 0.5)
  )

#projects per entity
entity_countsAF <- AF_info_IVs%>%
  count(Implementing_Agency, ietype1, name = "Project_CountAFEntity")

#visualize with names of entities to see which entities implement the most projects
ggplot(entity_countsAF, aes(x = reorder(Implementing_Agency, -Project_CountAFEntity), y =
Project_CountAFEntity, fill = ietype1)) +
  geom_bar(stat = "identity") +
  labs(
    title = "AF: Projects Implemented per Entity",
    x = "Implementing Entity",
    y = "Number of Projects Implemented"
```

```
  ) +
  theme_minimal() +
  scale_fill_manual(values = c(
    "National_DAE" = "#388E3C",  # blue
    "Regional" = "#8BC34A",  # orange
    "International"  = "#FFE082"   # green
  )) +
  coord_flip() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))


#STEP 4 create folder
# Create folder for PDFs based on excel file with PDF urls; only need to run if don't have a folder yet
dir.create("pdfs_AF_final", showWarnings = FALSE)

# Iterate through each row and download PDFs
for (i in 1:nrow(AF_info_IVs)) {
  url <- AF_info_IVs$`Document Content URL`[i]  # Adjust this column name

  if (is.na(url) || url == "") {
    cat("Skipping empty URL at row", i, "\n")
    next
  }

  # Extract a safe filename based on project details
  project_name <- gsub("[^a-zA-Z0-9_-]", "_", AF_info_IVs$`Family Name`[i])  # Modify based on actual column names
  file_name <- paste0(project_name, "_doc_", i, ".pdf")

  file_path <- file.path("pdfs_AF_final", file_name)

  # Check if URL is actually serving a PDF
  response <- HEAD(url)
  content_type <- headers(response)$`content-type`

  # Download the PDF
  tryCatch({
    GET(url, write_disk(file_path, overwrite = TRUE))
    cat("Downloaded:", file_name, "\n")
```

```
  }, error = function(e) {
    cat("Failed to download:", file_name, "\n")
  })
}

# Check downloaded files
list.files("pdfs_AF_final", full.names = TRUE)
#some still missing so need to manually add the pdfs if failed to properly download

###always do this step to help with matching dataframes later
AF_info_IVs$Local_PDF_Path <- paste0("pdfs_AF_final/",
                                     gsub("[^a-zA-Z0-9_-]", "_", AF_info_IVs$`Family Name`),
                                     "_doc_", 1:nrow(AF_info_IVs),
                                     ".pdf")

# STEP 5 extract text
#Now that the pdfs have been downloaded into a folder based on their urls, the text can be
extracted
pdf_folder <- "C:/Users/Sarah/Desktop/thesis/potential data use/pdfs_AF_final"

# Get a list of all PDFs in the folder
pdf_files <- list.files(pdf_folder, pattern = "\\.pdf$", full.names = TRUE)

# Initialize an error log
error_log <- data.frame(file_path = character(), error_message = character(), stringsAsFactors =
FALSE)

# Function to process each PDF
process_pdf <- function(file) {
  tryCatch({
    # Attempt to extract text normally
    text <- pdf_text(file)
    text_combined <- paste(text, collapse = " ")

    # If extracted text is mostly empty, assume it's a scanned PDF and use OCR
    if (nchar(text_combined) < 50) {  # Adjust threshold if needed
      message(paste("Using OCR for:", file))  # Debug message

      # Convert PDF pages to images
      images <- pdf_convert(file, dpi = 300)
```

```
      # Apply OCR to each image
      text_list <- lapply(images, function(img) ocr(img))

      # Combine all page texts
      text_combined <- paste(unlist(text_list), collapse = " ")
    }

    return(text_combined)

  }, error = function(e) {
    # Log errors
    error_log <<- rbind(error_log, data.frame(file_path = file, error_message = e$message,
stringsAsFactors = FALSE))
    return(NA)  # Return NA for failed extractions
  })
}

# Process all PDFs
extracted_text <- sapply(pdf_files, process_pdf)

# Create a dataframe with extracted text
AF_df_all <- data.frame(file_path = pdf_files, text = extracted_text, stringsAsFactors = FALSE)
#check that texted successfully extracted
sum(is.na(AF_df_all$text))

#STEP 6 KWIC
AF_corpus <- corpus(AF_df_all, text_field = "text")
docnames(AF_corpus) <- AF_df_all$file_path

#pre-process
AF_tokens <- tokens(AF_corpus,
                    remove_punct = TRUE,
                    remove_symbols = TRUE,
                    remove_numbers = TRUE)

AF_tokens <- tokens_remove(AF_tokens, stopwords("en"))

AF_tokens <- tokens_tolower(AF_tokens)
```

```
AF_context <- kwic(AF_tokens,
                pattern = phrase(c("local*", "exclu*", "international*", "injust*", "reject*",
"hierarch", "equal*", "inclus*", "marginali*", "minorit*", "communit*", "access*", "particip*",
"discriminat*", "civic", "indigenous", "subnational", "smallholders", "SMEs", "municipal",
"cooperative", "decentralized", "village", "household", "town", "province", "rural", "country
ownership", "flexib*", "accountab*", "gender", "race", "ethnic", "women", "inequal*",
"traditional knowledge", "tradition*", "custom*")),
                valuetype = "glob",
                window = 30)

corpus_AF_context <- corpus(AF_context)
docnames(corpus_AF_context)
# Tokenize the corpus while keeping it connected to the country observation
tokens_AF_context <- tokens(corpus_AF_context, remove_punct = TRUE,
                      remove_symbols = TRUE)

# Remove stopwords, lower case words
tokens_AF_context <- tokens_remove(tokens_AF_context, stopwords("en"))

dfm_AF_context <- dfm(tokens_AF_context,
                 tolower = TRUE,
                 verbose = TRUE)

# Perform stemming on dfm
dfm_AF <- dfm_wordstem(dfm_AF_context)

#Trim words that do not appear in at least 5% of documents or appear in more than 90% of
documents

dfm_AF_trim <- dfm_trim(dfm_AF,
                  min_docfreq = 0.05,
                  max_docfreq = 0.95,
                  docfreq_type = "prop")

# Ensure that countries are still correctly associated with each document

topfeatures(dfm_AF_trim, 30)
docnames(dfm_AF_trim)

#convert to dataframe to visualize
```

```
top_features_df <- data.frame(
  Feature = names(topfeatures(dfm_AF_trim, 30)),
  Frequency = topfeatures(dfm_AF_trim, 30)
)
top_features_df1 <- top_features_df %>%
  select(Frequency)

ggplot(top_features_df, aes(x = Feature, y = Frequency, fill = Feature)) +
  geom_bar(stat = "identity") +
  labs(
    title = "Top Features of AF KWIC",
    x = "Feature",
    y = "Frequency"
  ) +
  theme_minimal() +
  coord_flip() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

#STEP 7 SENTIMENT ANALYSIS APPLY DICTIONARY
# Apply Lexicoder sentiment dictionary  Young, L. & Soroka, S. (2012). Lexicoder Sentiment
Dictionary. Available at http://lexicoder.com.
AF_dfm_sent <- dfm_lookup(dfm_AF_trim, dictionary = data_dictionary_LSD2015)
print(AF_dfm_sent, 30)

AF_dfm_sent_df <- convert(AF_dfm_sent, to = "data.frame")
colnames(AF_dfm_sent_df)
# Aggregate sentiment scores by document
AF_dfm_sent_df <- data.frame(
  file_path = docnames(AF_dfm_sent),  # Original document names
  negative  = rowSums(AF_dfm_sent[, grep("negative", colnames(AF_dfm_sent))]),
  positive  = rowSums(AF_dfm_sent[, grep("positive", colnames(AF_dfm_sent))])
)

#need to make sure file paths are the same again (were renamed to include pre and post)
AF_dfm_sent_df <- AF_dfm_sent_df %>%
  mutate(base_file = sub("\\.\\d+\\.(pre|post)$", "", file_path))

AF_dfm_sent_df <- AF_dfm_sent_df %>%
  group_by(base_file) %>%
  summarize(
```

```
    negative = sum(negative),
    positive = sum(positive)
  ) %>%
  ungroup() %>%
  mutate(sentiment = positive - negative)

#no neg-negative or neg-positive values
#Calculate average sentiment per document

#AF_dfm_sent_df$file_path <- rownames(AF_dfm_sent_df)

#control for page numbers so average sentiment by page document
AF_dfm_sent_df <- AF_dfm_sent_df %>%
  mutate(sentiment = positive - negative) %>%
  select(base_file, sentiment)

AF_dfm_sent_df <- AF_dfm_sent_df %>%
  mutate(page_count = sapply(base_file, function(x) pdf_info(x)$pages))
summary(AF_dfm_sent_df$page_count)

average_sentiment_per_page_AF <- AF_dfm_sent_df %>%
  mutate(sentiment_per_pageAF = sentiment / page_count)

###STEP 8 MERGE WITH AF_INFO_IVS

AF_total <- AF_info_IVs %>%
  left_join(average_sentiment_per_page_AF, by = c("Local_PDF_Path" = "base_file"))

#file paths different lengths
average_sentiment_per_page_AF$file_path <-
basename(average_sentiment_per_page_AF$base_file)
AF_info_IVs$Local_PDF_Path <- basename(AF_info_IVs$Local_PDF_Path)

AF_total <- AF_info_IVs %>%
 left_join(average_sentiment_per_page_AF, by = c("Local_PDF_Path" = "file_path"))

#STEP 9 OLS REGRESSION

#need to prepare all controls for OLS
colnames(AF_total)
```

```
#filter and change to numerics
AF_total$duration <- as.numeric(gsub(" years", "", AF_total$duration))
AF_total <- AF_total %>%
  rename(duration_AF = duration)
AF_total$amount_disbursedAF <- as.numeric(gsub(",", "", AF_total$amount_disbursed))

AF_total <- AF_total %>%
  mutate(ietype_numericAF = ifelse(ietype == "NIE", 1,
                          ifelse(ietype == "RIE", 3,
                              ifelse(ietype == "MIE", 4, NA))))
#change to factor
class(AF_total$ietype_numericAF)
AF_total$ietype_factorAF <- as.factor(AF_total$ietype_numericAF)
#set national direct access entities as reference so can see impact per category
AF_total$ietype_factorAF <- relevel(AF_total$ietype_factorAF, ref = "1")
#change author type to numeric
AF_total <- AF_total %>%
  mutate(author_trimmed = trimws(author),
      author_numericAF = ifelse(author_trimmed == "Internal", 1,
                          ifelse(author_trimmed == "External", 2, NA)))

#add projects per country calculated earlier with visualization
#join
project_counts <- AF_total %>%
  count(Geographies, name = "Project_Count")
AF_total <- project_counts %>%
  left_join(AF_total, by = c("Geographies" = "Geographies"))
AF_total <- AF_total %>%
  rename(projects_per_countryAF = Project_Count)

#add projects per entity
entity_countsAF <- AF_total%>%
  count(Implementing_Agency, name = "Project_CountEntity")
AF_total <- entity_countsAF %>%
  left_join(AF_total, by = c("Implementing_Agency" = "Implementing_Agency"))
AF_total <- AF_total %>%
  rename(projects_per_entityAF = Project_CountEntity)

colnames(AF_total)
```

```
modelaf <- lm(sentiment_per_pageAF ~ ietype_factorAF + avg_climate_adaptation_score +
avg_civil_score + duration_AF + avg_fsi_score + amount_disbursedAF + author_numericAF +
projects_per_countryAF + projects_per_entityAF, data = AF_total)
summary(modelaf)

#visualize results

custom_ylabels1 <- c(
  "Projects per Entity",
  "Projects per Country",
  "Author Type",
  "Amount Disbursed (USD)", # Double check this name, should match summary
  "Avg FSI Score",
  "Duration",
  "Avg Civil Society Score",
  "Avg Climate Adaptation Score",
  "International Implementing Entity ", # Assuming 3 comes after 2 in the reversed order
  "Regional Implementing Entity",
  "National_direct_access (Constant)"
)

plot_model(modelaf,
           show.intercept = TRUE,
           axis.labels = custom_ylabels1,
           color = "navyblue") +
  labs(x = "Estimated Change in Sentiment per Page")

#STEP 10 MULTI-COLLINEARITY
#correlation matrix best for numeric and but ietype is a factor so unable to use and instead #can
do a boxplot
ggplot(AF_total, aes(x = ietype_factorAF, y = sentiment_per_pageAF)) +
  geom_boxplot() +
  labs(title = "AF: Sentiment Score Distribution by Implementing Entity Type",
       x = "Entity Type (Factor)",
       y = "Sentiment Score per Page") +
  theme_minimal()

#summary of implementing entity and mean and median sentiment
AFsummary <- data.frame(AF_total %>%
  group_by(ietype_factorAF) %>%
```

```
  summarise(
    mean_sentiment = mean(sentiment_per_pageAF, na.rm = TRUE),
    median_sentiment = median(sentiment_per_pageAF, na.rm = TRUE),
    count = n()
  ))

# Create the table
write.csv(AFsummary, "AFsummary.csv")

# multicollinearity
# Calculate VIFs
vif_valuesAF <- vif(modelaf)

# Print the VIF values
print(vif_valuesAF)

AFvifvalues <- data.frame(vif_valuesAF)

write.csv(AFvifvalues, "AFvifvalues.csv")

#STEP 11 HETEROSKEDASTICITY
#Breusch-Pagan Test
# Perform the Breusch-Pagan test
bptest_result <- bptest(modelaf)

# Print the results
print(bptest_result)

#fitted residuals plot
diagnostic_data <- data.frame(
  Fitted = fitted(modelaf),
  Residuals = residuals(modelaf)
)
ggplot(diagnostic_data, aes(x = Fitted, y = Residuals)) +
  geom_point(alpha = 0.6) +  # Plot the points (alpha for transparency)
  geom_hline(yintercept = 0, linetype = "dotted", color = "blue") + # Add horizontal line at 0
  geom_smooth(method = "loess", se = FALSE, color = "red", linetype = "dashed") + # Add a
smooth line (optional)
  labs(title = "AF Residuals vs Fitted Values",
       x = "Fitted Values (Predicted Response)",
```

```
    y = "Residuals (Observed - Predicted)") +
  theme_minimal()




#####GCF

#STEP 12 FILTER DATASETS
#filtering duplicated colnames
Project_documents_filteredGCF <- Project_documents %>%
  select(-which(duplicated(colnames(Project_documents))))

#english only text
Project_documents_filteredGCF <- Project_documents_filteredGCF %>%
  filter(Languages == "English")

#filter for GCF docs
Project_GCF <- Project_documents_filtered %>%
  filter(Source == "GCF")

#filter project per document,
GCF_1 <- Project_GCF %>%
  filter(grepl("Internal|External", author, ignore.case = TRUE))

#document type
GCF_1_<- GCF_1  %>%
  filter(`Document Type` == "Annual Performance Report" | `Document Type` == "Final
independent evaluation report")

#Add GCF entity data, check matching carefully

GCF_projects_info <- import("GCF_Projects_3_13_25.xlsx")
Entities_GCF <- import("GCF_entities_3_13_25.xlsx")

#filter to avoid confusion when merging
colnames(Entities_GCF)
Entities_GCF <- Entities_GCF %>%
  select(Entity, Name, DAE, Type, Stage, Size, Sector, `# Approved`)
```

```
GCF_info <- GCF_projects_info %>%
  left_join(Entities_GCF, by = c("Entity" = "Entity"))

GCF_2 <- GCF_1_ %>%
  left_join(GCF_info, by = c("Family Name" = "Project Name", "Geographies" = "Country
Codes"))
#filter to remove observations from 2024
GCF_3 <- GCF_2 %>%
  filter(`Start Year` != "2024")

#filter for multiple country observations (moved to after descriptive stats)
#GCF_4 <- GCF_3 %>%
#  separate_rows(Countries, sep = ",")

#STEP 13: ADD CONTROLS
#datasets already downloaded for AF

GCF_long <- GCF_3 %>%
  select(Project_Id, Geographies) %>%
  mutate(Geographies = str_trim(Geographies)) %>% #accounts for spacing
  separate_rows(Geographies, sep = ";\\s*")

GCF_long_scores <- GCF_long %>%
  left_join(civil_society_score, by = c("Geographies" = "iso3")) %>%
  left_join(gains_index, by = c("Geographies" = "iso3")) %>%
  left_join(FSI, by = c("Geographies" = "iso3"))

GCF_avg_scores <- GCF_long_scores %>%
  group_by(Project_Id) %>%
  summarise(
    avg_civil_score= mean(avg_civil_score, na.rm = TRUE),
    avg_climate_adaptation_score = mean(avg_climate_adaptation_score, na.rm = TRUE),
    avg_fcs_score = mean(avg_fsi_score, na.rm = TRUE),
    .groups = 'drop'
  ) %>%
  mutate(across(starts_with("avg_"), ~if_else(is.nan(.), NA_real_, .)))

GCF_6 <- GCF_3 %>%
  left_join(GCF_avg_scores, by = "Project_Id")
```

```
sum(is.na(GCF_6$avg_civil_score))
sum(is.na(GCF_6$avg_climate_adaptation_score))
sum(is.na(GCF_6$avg_fcs_score))
#NAs again introduced because FCS also doesn't include small island states like Tuvalu, the Marshall Islands, Tonga, Vanatu, Kiribati, Naura, Micronesia

#STEP 14 DESCRIPTIVE STATISTICS
#entities per filtered project
#categorize entites based on conditions
GCF_6 <- GCF_6 %>%
  mutate(entity_category = case_when(
    Type == "National" & DAE == TRUE  ~ 1,
    Type == "Regional" & DAE == TRUE  ~ 2,
    Type == "Regional" & DAE == FALSE ~ 3,
    Type == "International"          ~ 4,
    TRUE ~ NA_real_  # default fallback
  ))

#count entity totals per completed project
entity_countsGCF <- GCF_6 %>%
  select(Name, entity_category) %>%
  distinct() %>%  #
  mutate(
    National_DAE = str_detect(entity_category, "1"),
    Regional_DAE = str_detect(entity_category, "2"),
    Regional = str_detect(entity_category, "3"),
    International = str_detect(entity_category, "4")
  ) %>%
  summarise(
    National_DAE = sum(National_DAE),
    Regional_DAE = sum(Regional_DAE),
    Regional = sum(Regional),
    International = sum(International),
  ) %>%
  pivot_longer(everything(), names_to = "EntityType", values_to = "Count")

#calculate percentages for doughnut chart
entity_countsGCF <- entity_countsGCF %>%
  mutate(
    percent = Count / sum(Count),
```

```
    label = paste0(round(percent * 100), "%")
  )
#create doughnut chart
ggplot(entity_countsGCF, aes(x = 2, y = Count, fill = EntityType)) +
  geom_bar(stat = "identity", width = 1, color = "white") +
  coord_polar(theta = "y") +
  xlim(0.5, 2.8) +
  geom_text(aes(x = 2.75, label = label),  # bump x outwards
            position = position_stack(vjust = 0.5),
            size = 4, color = "black") +
  theme_void() +
  scale_fill_manual(values = c(
    "National_DAE" = "#388E3C",
    "Regional_DAE" = "darkgreen",
    "Regional"  = "#8BC34A",
    "International" = "#FFE082"
  )) +
  theme(legend.position = "right") +
  ggtitle("Green Climate Fund") +
  theme(plot.title = element_text(hjust = 0.5))

#total funding disbursed per project
GCF_6$entity_category <- as.factor(GCF_6$entity_category)

#renaming to properly fill colors in ggplot
GCF_6$entity_category1 <- fct_recode(GCF_6$entity_category,
                                      "National_DAE" = "1",
                                      "Regional_DAE" = "2",
                                      "Regional" = "3",
                                      "International" = "4"
)

funding_by_ieGCF <- GCF_6 %>%
  select(Name, entity_category1, `FA Financing`) %>%
  distinct() %>%  # Remove exact duplicates of Name + category + amount otherwise the
information is inflated
  group_by(entity_category1) %>%
  summarise(total_disbursed = sum(`FA Financing`, na.rm = TRUE), .groups = "drop")

#get percent
```

```
funding_by_ieGCF1 <- funding_by_ieGCF %>%
  mutate(
    percent = total_disbursed / sum(total_disbursed),
    label = paste0(round(percent * 100), "%")
  )
ggplot(funding_by_ieGCF1, aes(x = 2, y = total_disbursed, fill = entity_category1)) +
  geom_bar(stat = "identity", width = 1, color = "white") +
  coord_polar(theta = "y") +
  xlim(0.5, 2.8) +
  geom_text(aes(x = 2.75, label = label),  # bump x outwards
            position = position_stack(vjust = 0.5),
            size = 4, color = "black") +
  theme_void() +
  scale_fill_manual(values = c(
    "National_DAE" = "#388E3C",
    "Regional_DAE" = "darkgreen",
    "Regional"  = "#8BC34A",
    "International" = "#FFE082"
  )) +
  theme(legend.position = "right") +
  ggtitle("GCF: Total Funding Disbursed by Implementing Entity") +
  theme(plot.title = element_text(hjust = 0.5))
funding_by_ieGCF2 <- GCF_6 %>%
  select(Name, entity_category1, `FA Financing`) %>%
  distinct() %>%  # Remove exact duplicates of Name + category + amount otherwise the
information is inflated
  group_by(Name, entity_category1) %>%
  summarise(total_disbursed = sum(`FA Financing`, na.rm = TRUE), .groups = "drop")

#visualize with names of entities to see which entities receive the most funding in a bar chart
#based on 44 entities who have received funding for projects
ggplot(funding_by_ieGCF2, aes(x = reorder(Name, -total_disbursed), y = total_disbursed, fill =
entity_category1)) +
  geom_bar(stat = "identity") +
  labs(
    title = "GCF: Funding Received by Implementing Entity",
    x = "Implementing Entity",
    y = "Funding Disbursed (USD)"
  ) +
  theme_minimal() +
```

```
  scale_fill_manual(values = c(
    "National_DAE" = "#388E3C",
    "Regional_DAE" = "darkgreen",
    "Regional"  = "#8BC34A",
    "International" = "#FFE082"
  )) +
  coord_flip() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

#author type visual
#count author type
author_typeGCF <- GCF_6 %>%
  select(author, Project_Id, Countries, entity_category1) %>%
  distinct() %>% #remove duplicates, do i include country names or not to filter
  mutate(
    External = str_detect(author, "External"),
    Internal = str_detect(author, "Internal")
  ) %>%
  summarise(
    External = sum(External),
    Internal = sum(Internal)
  ) %>%
  pivot_longer(everything(), names_to = "Authortype", values_to = "Count")

#create pie chart
author_type2 <- author_typeGCF %>%
  mutate(
    percent = Count / sum(Count),
    label = paste0(round(percent * 100), "%")
  )
ggplot(author_type2, aes(x = 2, y = Count, fill = Authortype)) +
  geom_bar(stat = "identity", width = 1, color = "white") +
  coord_polar(theta = "y") +
  xlim(0.5, 2.8) +
  geom_text(aes(x = 2.75, label = label),  # bump x outwards
            position = position_stack(vjust = 0.5),
            size = 4, color = "black") +
  theme_void() +
  scale_fill_manual(values = c(
    "External" = "navy",  # blue
```

```
    "Internal" = "skyblue"  # orange
  )) +
  theme(legend.position = "right") +
  ggtitle("Green Climate Fund") +
  theme(plot.title = element_text(hjust = 0.5))

#Project duration (estimation since no project completed yet except for two)
duration_GCF <- GCF_6 %>%
  select(`Duration (years)`, Name, entity_category1, Project_Id) %>%
  distinct()

avg_duration <- duration_GCF %>%
  group_by(entity_category1) %>%
  summarise(avg_duration = mean(`Duration (years)`, na.rm = TRUE))

ggplot(avg_duration, aes(x = entity_category1, y = avg_duration, fill = entity_category1)) +
  geom_col() +
  labs(title = "GCF: Average Project Duration by Entity Type",
       x = "Entity Type", y = "Average Duration (Years)") +
  theme_minimal() +
  scale_fill_manual(values = c(
    "National_DAE" = "#388E3C",
    "Regional_DAE" = "darkgreen",
    "Regional"  = "#8BC34A",
    "International" = "#FFE082"
  )) +
  theme(legend.position = "none")

#projects per country
country_per_project <- GCF_6 %>%
  group_by(entity_category1) %>%
  summarise(avg_country_per_project = mean(Countries_per_project, na.rm = TRUE))

#visual of projects per country
GCF_7 <- GCF_6 %>%
 separate_rows(Geographies, sep = ";")

world <- ne_countries(scale = "medium", returnclass = "sf")

project_countsGCF <- GCF_7 %>%
```

```
  count(Geographies, name = "GCFProject_Count")
summary(project_countsGCF$GCFProject_Count)
world_data <- world %>%
  left_join(project_countsGCF, by = c("iso_a3_eh" = "Geographies"))

breaks <- c(0, 3, 5, 7, 9, 11, 13)

ggplot(world_data) +
  geom_sf(aes(fill = GCFProject_Count), color = "white", size = 0.2) +
  scale_fill_gradient(
    name = "Number of Projects",
    low = "lightgreen",    # light green
    high = "darkgreen",   # dark green
    na.value = "grey90", # for countries with no data
    breaks = breaks
  ) +
  theme_minimal() +
  labs(title = "GCF Filtered Project Geographic Distribution") +
  theme(
    legend.position = "right",
    plot.title = element_text(hjust = 0.5)
  )

#projects per entity
entity_countsGCF <- GCF_6 %>%
  count(Name, entity_category1, name = "Project_CountGCFEntity")

#visualize with names of entities to see which entities implement the most projects
ggplot(entity_countsGCF, aes(x = reorder(Name, -Project_CountGCFEntity), y =
Project_CountGCFEntity, fill = entity_category1)) +
  geom_bar(stat = "identity") +
  labs(
    title = "GCF: Projects Implemented per Entity",
    x = "Implementing Entity",
    y = "Number of Projects Implemented"
  ) +
  theme_minimal() +
  scale_fill_manual(values = c(
    "National_DAE" = "#388E3C",
    "Regional_DAE" = "#8BC34A",
```

```
    "Regional"  = "darkgreen",
    "International" = "#FFE082"
  )) +
  coord_flip() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
summary(entity_countsGCF$Project_CountGCFEntity)

#STEP 15: EXTRACT TEXT FROM DOCUMENTS
# Create folder for PDFs; only need to run if don't have a folder yet
dir.create("pdfs_GCF_final", showWarnings = FALSE)

# Iterate through each row and download PDFs
for (i in 1:nrow(GCF_6)) {
  url <- GCF_6$`Document Content URL`[i]  # Adjust this column name

  if (is.na(url) || url == "") {
    cat("Skipping empty URL at row", i, "\n")
    next
  }

  # Extract a safe filename based on project details
  project_name <- gsub("[^a-zA-Z0-9_-]", "_", GCF_6$`Family Name`[i])  # Modify based on
actual column names
  file_name <- paste0(project_name, "_doc_", i, ".pdf")

  file_path <- file.path("pdfs_GCF_final", file_name)

  # Check if URL is actually serving a PDF
  response <- HEAD(url)
  content_type <- headers(response)$`content-type`

  # Download the PDF
  tryCatch({
    GET(url, write_disk(file_path, overwrite = TRUE))
    cat("Downloaded:", file_name, "\n")
  }, error = function(e) {
    cat("Failed to download:", file_name, "\n")
  })
}
```

```
# Check downloaded files
list.files("pdfs_GCF_final", full.names = TRUE)

#always do this step to ensure correct labelling even if pdfs already downloaded
GCF_6$Local_PDF_Path <- paste0("pdfs_GCF_final/",
                               gsub("[^a-zA-Z0-9_-]", "_", GCF_6$`Family Name`),
                               "_doc_", 1:nrow(GCF_6),
                               ".pdf")

# 1. List of expected file paths TEST
expected_pdf_paths <- GCF_6$Local_PDF_Path
expected_basenames <- basename(expected_pdf_paths)

# 2. List of actual PDF files
actual_pdf_files <- list.files("pdfs_GCF_final", full.names = TRUE)
actual_basenames <- basename(actual_pdf_files)

# 3. Find the missing basenames
missing_basenames <- setdiff(expected_basenames, actual_basenames)
cat("Missing PDF Basenames:\n")
print(missing_basenames)
#ABOVE only do once
#need to be cautious of renaming so all different from above
pdf_folder_GCF <- "C:/Users/Sarah/Desktop/thesis/potential data use/pdfs_GCF_final"

# Get a list of all PDFs in the folder
pdf_files_GCF <- list.files(pdf_folder_GCF, pattern = "\\.pdf$", full.names = TRUE)

# Initialize an error log
error_log_1 <- data.frame(file_path = character(), error_message = character(), stringsAsFactors
= FALSE)

# Extract text from PDFs
extracted_text <- sapply(pdf_files_GCF, function(file) {
  tryCatch({
    text <- pdf_text(file)  # Extract text
    paste(text, collapse = " ")  # Combine all pages into one string
  }, error = function(e) {
    # Log the error with file path and error message
```

```
    error_log <<- rbind(error_log_1, data.frame(file_path = file, error_message = e$message,
stringsAsFactors = FALSE))
    return(NA)  # Return NA for failed extractions
  })
})

# Create a dataframe with extracted text
pdf_text_df_GCF <- data.frame(file_path = pdf_files_GCF, text = extracted_text,
stringsAsFactors = FALSE)

sum(is.na(pdf_text_df_GCF$text))
#below tries to download scanned pdfs
pdf_folder_1 <- "C:/Users/Sarah/Desktop/thesis/potential data use/pdfs_GCF_final"

# Get a list of all PDFs in the folder
pdf_files_1 <- list.files(pdf_folder_1, pattern = "\\.pdf$", full.names = TRUE)

# Initialize an error log
error_log_2 <- data.frame(file_path = character(), error_message = character(), stringsAsFactors
= FALSE)

# Function to process each PDF
process_pdf <- function(file) {
  tryCatch({
    # Attempt to extract text normally
    text <- pdf_text(file)
    text_combined <- paste(text, collapse = " ")

    # If extracted text is mostly empty, assume it's a scanned PDF and use OCR
    if (nchar(text_combined) < 50) {  # Adjust threshold if needed
      message(paste("Using OCR for:", file))  # Debug message

      # Convert PDF pages to images
      images <- pdf_convert(file, dpi = 300)

      # Apply OCR to each image
      text_list <- lapply(images, function(img) ocr(img))

      # Combine all page texts
      text_combined <- paste(unlist(text_list), collapse = " ")
```

```
    }

    return(text_combined)

  }, error = function(e) {
    # Log errors
    error_log <<- rbind(error_log_2, data.frame(file_path = file, error_message = e$message,
stringsAsFactors = FALSE))
    return(NA)  # Return NA for failed extractions
  })
}

#Process all PDFs
extracted_text <- sapply(pdf_files_1, process_pdf)

# Create a dataframe with extracted text
GCF_df <- data.frame(file_path = pdf_files_1, text = extracted_text, stringsAsFactors = FALSE)

#check extracted text
sum(is.na(GCF_df$text))

#STEP 16 KWIC
#pre-processing
GCF_corpus <- corpus(GCF_df, text_field = "text")
docnames(GCF_corpus) <- GCF_df$file_path

#tokenizing
GCF_tokens <- tokens(GCF_corpus,
                     remove_punct = TRUE,
                     remove_symbols = TRUE,
                     remove_numbers = TRUE)

GCF_tokens <- tokens_remove(GCF_tokens, stopwords("en"))

GCF_tokens <- tokens_tolower(GCF_tokens)

#apply KWIC
GCF_context <- kwic(GCF_tokens,
                    pattern = phrase(c("local*", "exclu*", "international*", "injust*", "reject*",
"hierarch", "equal*", "inclusi*", "marginali*", "minorit*", "communit*", "access*", "particip*",
```

```
"discriminat*", "civic", "indigenous", "subnational", "smallholders", "SMEs", "municipal",
"cooperative", "decentralized", "village", "household", "town", "province", "rural", "country
ownership", "flexib*", "accountab*", "gender", "race", "ethnic", "women", "inequal*",
"traditional knowledge", "tradition*", "custom*")),
                    valuetype = "glob",
                    window = 30)

corpus_GCF_context <- corpus(GCF_context)
docnames(corpus_GCF_context)
# Tokenize the corpus while keeping it connected to the country observation
tokens_GCF_context <- tokens(corpus_GCF_context, remove_punct = TRUE,
                             remove_symbols = TRUE)

# Remove stopwords, lower case words
tokens_GCF_context <- tokens_remove(tokens_GCF_context, stopwords("en"))

dfm_GCF_context <- dfm(tokens_GCF_context,
                       tolower = TRUE,
                       verbose = TRUE)

# Perform stemming on dfm
dfm_GCF_1 <- dfm_wordstem(dfm_GCF_context)

#Trim words that do not appear in at least 5% of documents or appear in more than 90% of
documents

dfm_GCF_trim_1 <- dfm_trim(dfm_GCF_1,
                         min_docfreq = 0.05,
                         max_docfreq = 0.95,
                         docfreq_type = "prop")

topfeatures(dfm_GCF_trim_1, 30)
docnames(dfm_GCF_trim_1)

#convert to dataframe to visualize
top_features_GCF <- data.frame(
  Feature = names(topfeatures(dfm_GCF_trim_1, 30)),
  Frequency = topfeatures(dfm_GCF_trim_1, 30)
)
top_features_GCF1 <- top_features_GCF %>%
```

```
  select(Frequency)

ggplot(top_features_GCF, aes(x = Feature, y = Frequency, fill = Feature)) +
  geom_bar(stat = "identity") +
  labs(
    title = "Top Features of GCF KWIC",
    x = "Feature",
    y = "Frequency"
  ) +
  theme_minimal() +
  coord_flip() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))

#STEP 17 SENTIMENT ANALYSIS
# Apply Lexicoder sentiment dictionary Young, L. & Soroka, S. (2012). Lexicoder Sentiment
Dictionary. Available at http://lexicoder.com.
GCF_dfm_sent <- dfm_lookup(dfm_GCF_trim_1, dictionary = data_dictionary_LSD2015)
print(GCF_dfm_sent, 30)

GCF_dfm_sent_df <- convert(GCF_dfm_sent, to = "data.frame")
colnames(GCF_dfm_sent_df)
# Aggregate sentiment scores by document
GCF_dfm_sent_df <- data.frame(
  file_path = docnames(GCF_dfm_sent),  # Original document names
  negative  = rowSums(GCF_dfm_sent[, grep("negative", colnames(GCF_dfm_sent))]),
  positive  = rowSums(GCF_dfm_sent[, grep("positive", colnames(GCF_dfm_sent))])
)

#need to make sure file paths are the same again (were renamed to include pre and post)
GCF_dfm_sent_df <- GCF_dfm_sent_df %>%
  mutate(base_file = sub("\\.\\d+\\.(pre|post)$", "", file_path))

GCF_dfm_sent_1 <- GCF_dfm_sent_df %>%
  group_by(base_file) %>%
  summarize(
    negative = sum(negative),
    positive = sum(positive)
  ) %>%
  ungroup() %>%
  mutate(sentiment = positive - negative)
```

```
#no neg-negative or neg-positive values
#AF_dfm_sent_df$file_path <- rownames(AF_dfm_sent_df)

#control for page numbers so average sentiment by page document
GCF_dfm_sent_2 <- GCF_dfm_sent_1 %>%
  mutate(sentiment = positive - negative) %>%
  select(base_file, sentiment)

GCF_dfm_sent_3 <- GCF_dfm_sent_2 %>%
  mutate(page_count = sapply(base_file, function(x) pdf_info(x)$pages))
summary(GCF_dfm_sent_3$page_count)

GCF_average_sentiment_per_page <- GCF_dfm_sent_3 %>%
  mutate(sentiment_per_pageGCF = sentiment / page_count)
#page count is 3 to 246

sum(is.na(GCF_average_sentiment_per_page$sentiment_per_page))
###NOW MERGE WITH GCF_6
#file paths different lengths
GCF_average_sentiment_per_page$file_path <-
basename(GCF_average_sentiment_per_page$base_file)
GCF_6$Local_PDF_Path <- basename(GCF_6$Local_PDF_Path)

GCF_total <- GCF_6 %>%
  left_join(GCF_average_sentiment_per_page, by = c("Local_PDF_Path" = "file_path"))

#checking that datasets merged properly
sum(is.na(GCF_total$sentiment_per_pageGCF))

# GCF_average_sentiment_per_page %>% filter(is.na(matched_GCF7_key)) %>%
select(sentiment_basename) %>% head()

#STEP 18 OLS REGRESSION
#add/check necessary independent variables
#regression attempt
colnames(GCF_total)

#filter and change to numerics
GCF_total$DurationGCF <- as.numeric(GCF_total$`Duration (years)`)
```

```
GCF_total$Financing_disbursedGCF <- as.numeric(GCF_total$`FA Financing`)

GCF_total <- GCF_total %>%
  mutate(entity_categoryGCF = case_when(
    Type == "National" & DAE == TRUE  ~ 1,
    Type == "Regional" & DAE == TRUE  ~ 2,
    Type == "Regional" & DAE == FALSE ~ 3,
    Type == "International"          ~ 4,
    TRUE ~ NA_real_  # default fallback
  ))

#change to factor
class(GCF_total$entity_categoryGCF)
GCF_total$entity_categoryfactorGCF <- as.factor(GCF_total$entity_categoryGCF)
#set national direct access entities as reference so can see impact per category
GCF_total$entity_categoryfactorGCF <- relevel(GCF_total$entity_categoryfactorGCF, ref =
"1")

#author type make numeric
GCF_total <- GCF_total %>%
  mutate(author_numericGCF = ifelse(author == "Internal", 1,
                                ifelse(author == "External", 2, NA)))
#add project_countsGCF
project_countsGCF <- GCF_total %>%
  count(Geographies, name = "Project_per_countryGCF")
GCF_total <- GCF_total %>%
  left_join(project_countsGCF, by = c("Geographies" = "Geographies"))

#add projects per entity (how experienced are they)
entity_countsGCF <- GCF_total%>%
  count(Name, name = "Project_per_EntityGCF")
GCF_total <- GCF_total %>%
  left_join(entity_countsGCF, by = c("Name" = "Name"))

colnames(GCF_total)
#countries_per_project has perfect collinearity with all the country controls so appears as NA
modelGCF <- lm(sentiment_per_pageGCF ~ entity_categoryfactorGCF +
avg_climate_adaptation_score + `avg_civil_score` + avg_fcs_score + DurationGCF +
```

```
Financing_disbursedGCF + author_numericGCF + Project_per_countryGCF +
Project_per_EntityGCF, data = GCF_total)
summary(modelGCF)

#visualize results
custom_ylabels2 <- c(
  "Projects per Entity",
  "Projects per Country",
  "Author Type",
  "Amount Disbursed (USD)",
  "Avg FSI Score",
  "Duration",
  "Avg Civil Society Score",
  "Avg Climate Adaptation Score",
  "International Implementing Entity ",
  "Regional Direct Access Implementing Entity",
  "National_direct_access (Constant)"
)

plot_model(modelGCF,
           colors = "navyblue",
           show.intercept = TRUE,
          axis.labels = custom_ylabels2) +
 # labs(x = "Estimated Change in Sentiment per Page")

#visualize both model results
stargazer(modelaf, modelGCF,
          align = TRUE,
          type = "html",
          title = "AF and GCF Regression Table",
          style = "qje",
          out = "AF_GCF_regression_table_2.doc")

write.csv(modelGCF, "modelGCF.csv")

#STEP 19 MULTI-COLLINEARITY

#boxplot to see relationship between entity type and sentiment for GCF
boxplot <- ggplot(GCF_total, aes(x = entity_categoryfactorGCF, y = sentiment_per_pageGCF))
+
```

```
  geom_boxplot() +
  labs(title = "GCF: Sentiment Score Distribution by Implementing Entity Type",
       x = "Entity Type",
       y = "Sentiment Score per Page") +
  theme_minimal()

#summary of implementing entity and meean and median sentiment
GCFsummary <- data.frame(GCF_total %>%
                           group_by(entity_categoryfactorGCF) %>%
                           summarise(
                             mean_sentiment = mean(sentiment_per_pageGCF, na.rm = TRUE),
                             median_sentiment = median(sentiment_per_pageGCF, na.rm = TRUE),
                             count = n()
                           ))

write.csv(GCFsummary,"GCFsummary.csv")
# Create the table

# Calculate VIFs
vif_valuesGCF <- vif(modelGCF)
print(vif_valuesGCF)
GCFvifvalues <- data.frame(vif_valuesGCF)
write.csv(GCFvifvalues,"GCFvifvalues.csv")

#STEP 20 HETEROSKEDASTICITY

#Breusch-Pagan Test
# Perform the Breusch-Pagan test
bptest_resultGCF <- bptest(modelGCF)

# Print the results
print(bptest_resultGCF)

#visualize plotted residuals
diagnostic_data <- data.frame(
  Fitted = fitted(modelGCF),
  Residuals = residuals(modelGCF)
)
ggplot(diagnostic_data, aes(x = Fitted, y = Residuals)) +
  geom_point(alpha = 0.6) +  # Plot the points (alpha for transparency)
```

```
  geom_hline(yintercept = 0, linetype = "dotted", color = "blue") + # Add horizontal line at 0
  geom_smooth(method = "loess", se = FALSE, color = "red", linetype = "dashed") + # Add a
smooth line (optional)
  labs(title = "GCF Residuals vs Fitted Values",
       x = "Fitted Values (Predicted Response)",
       y = "Residuals (Observed - Predicted)") +
  theme_minimal()

#STEP 21 SUMMARIZE ALL VARIABLES IN SUMMARY STATISTICS TABLE

# Create an empty data frame to store summary statistics
summary_table_df <- data.frame(
  Variable = character(),
  Mean = numeric(),
  `Std. Dev.` = numeric(),
  Min. = numeric(),
  Max. = numeric(),
  N = integer(),
  stringsAsFactors = FALSE
)

# Function to calculate summary statistics for a vector
get_summary_stats <- function(x, out_name) {
  if (is.numeric(x)) {
    data.frame(
      Variable = out_name,
      Mean = mean(x, na.rm = TRUE),
      `Std. Dev.` = sd(x, na.rm = TRUE),
      Min. = min(x, na.rm = TRUE),
      Max. = max(x, na.rm = TRUE),
      N = sum(!is.na(x)), # Count non-NA values
      stringsAsFactors = FALSE
    )
  } else {
    # For non-numeric variables (like factors or characters),
    # we typically only report the number of non-missing observations (N).
    # Mean, Std. Dev., Min, Max are not applicable, so we set them to NA.
    data.frame(
      Variable = out_name,
      Mean = NA,
```

```
      `Std. Dev.` = NA,
      Min. = NA,
      Max. = NA,
      N = sum(!is.na(x)), # Count non-NA values
      stringsAsFactors = FALSE
    )
  }
}

# List of variables
summary(AF_total$ietype_numericAF)
variables_info <- list(
  AF_total = list(
    list(col_name = "ietype_numericAF", out_name = "implementing_entity_typeAF"), # Original
column ietype1
    list(col_name = "amount_disbursedAF", out_name = "amount_disbursedAF"),
    list(col_name = "author_numericAF", out_name = "author_typeAF"), # Original column
author_numericAF
    list(col_name = "projects_per_entityAF", out_name = "projects_per_entityAF"),
    list(col_name = "projects_per_countryAF", out_name = "projects_per_countryAF"),
    list(col_name = "sentiment_per_pageAF", out_name = "sentiment_per_pageAF")
  ),
  GCF_total = list(
    list(col_name = "entity_categoryGCF", out_name = "implementing_entity_typeGCF"), #
Original column entity_categoryGCF
    list(col_name = "Financing_disbursedGCF", out_name = "Financing_disbursedGCF"),
    list(col_name = "author_numericGCF", out_name = "author_typeGCF"), # Original column
author_numericGCF
    list(col_name = "Project_per_EntityGCF", out_name = "Project_per_EntityGCF"),
    list(col_name = "Project_per_countryGCF", out_name = "Project_per_countryGCF"),
    list(col_name = "sentiment_per_pageGCF", out_name = "sentiment_per_pageGCF")
  ),
  civil_society_score = list(
    list(col_name = "avg_civil_score", out_name = "avg_civil_score")
  ),
  FSI = list(
    list(col_name = "avg_fsi_score", out_name = "avg_fsi_score")
  ),
  gains_index = list(
```

```
    list(col_name = "avg_climate_adaptation_score", out_name =
"avg_climate_adaptation_score")
  )
)

# Loop through each data frame and its specified variables
for (df_name in names(variables_info)) {
  df <- get(df_name) # Get the data frame object by its name

  for (var_info in variables_info[[df_name]]) {
    col_name <- var_info$col_name # The actual column name in the data frame
    out_name <- var_info$out_name # The desired name in the output table

    # Check if the column exists in the data frame
    if (col_name %in% colnames(df)) {
      col_data <- df[[col_name]] # Get the column data
      stats_row <- get_summary_stats(col_data, out_name)
      summary_table_df <- rbind(summary_table_df, stats_row)
    } else {
      # If the column is not found, add a row with N=0 and NA for other stats
      summary_table_df <- rbind(summary_table_df, data.frame(
        Variable = out_name,
        Mean = NA,
        `Std. Dev.` = NA,
        Min. = NA,
        Max. = NA,
        N = 0,
        stringsAsFactors = FALSE
      ))
      warning(paste("Column '", col_name, "' not found in data frame '", df_name, "'", sep = ""))
    }
  }
}

write.csv(summary_table_df, "summary_statistics2.csv")
#
#
###END
```