The Distributional Consequences of Regime Complexity: Evidence from Multilateral Climate Finance

Isabella Bellezza[1]
Ayse Kaya[2]

January 6, 2026

Abstract

Global governance increasingly operates through regime complexes —overlapping institutions that interact within an issue area—yet, while prior work has emphasized their implications for international cooperation, we know little about how the structure of this complexity shapes distributive outcomes. Conceptualizing regime complexes as networks of interacting international organizations (IOs), we argue that exposure to well-connected IOs provides states with informational advantages that improve access to the goods these regimes supply. We evaluate this theory using original project-level data on multilateral climate finance from 2010–2021 and show that recipient states with greater exposure to well-connected donor IOs—those with many co-financing relationships ("hubs") and those bridging otherwise disconnected donor groups ("brokers")—receive substantially more climate finance projects, even after adjusting for recipient and donor characteristics and selection into the regime. These advantages are especially pronounced for poorer developing countries. By bridging work on social network analysis and regime complexity, this study advances our understanding of how the shifting topology of governance structures shapes who benefits from them.

[1]Department of Political Science, Northwestern University
[2]Department of Political Science, Swarthmore College

1 Introduction

International Relations has long recognized that global governance is becoming more "complex" as a growing number of international organizations (IOs) increasingly govern a single issue area (Alter and Meunier, 2009; Raustiala and Victor, 2004; Gehring and Faude, 2013). An extensive literature has detailed how resulting "regime complexes"emerge and evolve, and – the topic of this article – how they affect outcomes (Alter and Raustiala, 2018; Henning and Pratt, 2023; Eilstrup-Sangiovanni and Westerwinter, 2022; Heldt and O., 2024; Yu and Xue, 2019).[3] Scholars in this research program have examined especially whether complexity helps or hinders global governance, focusing extensively on outcomes related to the mechanics of governance, such as cooperation, rule compliance, and accountability.[4] Less well-understood, however, is how the structure of complex regimes impacts the *distribution of goods* that the regime provides, such as who receives how much development assistance. How does the proliferation of IOs working in the same domain, and the changing interrelations between them, impact states that rely on the regime for critical goods, such as climate finance? How, in short, do preexisting relationships among IOs affect distributive outcomes, particularly for potential beneficiary states most in need?

To examine how the dynamic structure of complex regimes impacts the distribution of goods, we draw on social network analysis (SNA). SNA provides a framework for mapping and analyzing patterns of ties among ac-

[3]We define these complexes as "a set of international institutions that operate in a common issue area and the (formal and informal) mechanisms that coordinate them" (Henning and Pratt, 2023, 2181).

[4]For example, scholarship in this tradition has shown that the fragmentation of governance across multiple institutions blurs authority and accountability (Alter and Meunier, 2009; Widerberg and Pattberg, 2016), and dissatisfied states may strategically leverage multiple institutions to challenge the rules, practices, and missions of existing ones (Clark, 2022; Drezner, 2009; Verdier, 2022). Complexity, however, may increase flexibility as it increases the number of providers on the international scene (Keohane and Victor, 2010; Orsini and Young, 2013).

tors, revealing both the structural properties of a system and the relational positions of its participants. This is particularly well suited for studying regime complexes, which are, by definition, characterized by overlapping institutions. Although existing efforts to typologize the architecture of regime complexes draw on network concepts like "hierarchy" (Henning and Pratt, 2023) and "density" (Eilstrup-Sangiovanni and Westerwinter, 2022), there remains much room for engagement with a well-established body of network measurement and theory associated with those – and other – network concepts developed precisely to operationalize social structure (Wasserman and Faust, 1994; Rawlings et al., 2023).[5] In bridging these two relevant but largely disconnected literatures, we conceptualize regime complexes as networks and theorize how dynamic *patterns of interaction* among IOs – rather than attributes of those IOs – shape distributive outcomes, namely which states receive the key goods that the regime provides.

We argue that recipient states exposed to well-connected donor IOs benefit most from the regime by improving the recipients' information environment. Just as an advisee with a well-connected mentor may receive more opportunities than an equally talented peer with an isolated mentor, states linked to well-connected donors may gain disproportionate advantages, all else being equal. In regimes that distribute financing, whether for security or the environment, we argue that donor IOs function as access points that connect recipients to the broader donor network. These IOs differ in their ability to facilitate access to new financing because they occupy different positions within the network, which affects their ability to supply valuable *information* to, and about, their recipients. Well-connected donors can both improve the information a recipient receives about other donors (for exam-

[5]See (Chelminski, Andonova and Sun, 2022) for an application of network analysis to explain the emergence of the clean energy regime complex. While that work analyzes networks as a consequence, we are interested in networks as a cause. Green (2022) also uses social network analysis to descriptively map the Antarctic regime complex, but we are interested in exploring distributive outcomes.

ple, regarding project design, standards, and funding priorities) and enhance the information about the recipient for donors (for example, strengthening signals about a recipient's credibility as a borrower). Thus, we expect that (1) being funded by IOs that are central in a regime complex – defined both in terms of the quantity of relationships an IO has with other IOs and the extent to which an IO bridges disconnected clusters of IOs in the complex – improves states' subsequent ability to secure new funding. Moreover, we expect (2) that the benefits of such access are especially valuable for poorer developing countries compared to wealthier developing countries.

We evaluate these expectations using the case of multilateral climate finance, defined as funding to reduce greenhouse gas emissions and adapt to climate change that is pooled from multiple countries and disbursed through IOs, like multilateral development banks (MDBs) as well as dedicated multilateral climate funds. Though climate finance includes both public and private flows (Andonova, Betsill and Bulkeley, 2009; Michaelowa and Michaelowa, 2017), we focus only on *public* funds channeled *multilaterally* through international organizations. We focus on public funds because they constitute the largest and most stable source of dedicated climate funding, particularly for low-income countries that need this financing the most.[6] We focus on multilateral financing because the available data are more consistent and reliable than for bilateral financing.[7]

We map the network of multilateral climate finance by identifying the co-financing ties that exist between different IOs. Co-financing occurs when two or more IOs provide investment finance for the same climate change-

[6]According to the OECD, public funds from both bilateral and multilateral channels continue to make up the bulk of climate finance, accounting for 80% of the total (OECD, 2025).

[7]While OECD data on bilateral climate finance have been criticized for methodological inconsistencies (Michaelowa and Michaelowa, 2011), the OECD tracks multilateral flows using a different approach, applies a common methodology developed by multilateral development banks in 2011, and further improves on IOs' own reporting by independently verifying reported amounts and flagging cases where no expected climate change impact is found. We also augment the OECD dataset (see Section 3).

related project. Compared to alternative operationalizations of ties between IOs, such as memoranda of understanding, co-financing captures actual (as opposed to de jure or assumed) ties between IOs within the network.[8] More importantly for our theory, when IOs co-finance at the project level, they exchange information about project design, implementation standards, and recipient performance. This is valuable knowledge that bears on future funding decisions and may be passed on to the recipients they finance. Individual IOs, however, differ in how they participate in these co-financing relationships. Some collaborate widely and repeatedly with many other donors, accumulating large volumes of experience through dense patterns of joint project work. We refer to these organizations as hubs. Other IOs collaborate across otherwise weakly connected groups of donors, gaining exposure to distinct donor communities, standards, and practices. We refer to these organizations as brokers.

To estimate the effect of recipient exposure to hubs and brokers on subsequent project allocation, we estimate a series of two-stage Heckman models that draws on project-level multilateral climate finance data from the OECD from 2010 to 2021.[9] In line with our theoretical expectations, we find that recipient exposure to hub and broker IOs significantly increases the amount of climate finance recipients subsequently receive, but these benefits are especially pronounced for lower-income recipients. The findings demonstrate that access to well-connected donors yields substantially more climate finance projects for poorer countries, with the marginal effect of network exposure declining as income rises. The core findings are robust across alternative

[8] Co-financing captures the formal pooling of financial resources and technical expertise in pursuit of a shared intervention (Clark, 2025).

[9] Our unit of analysis is the *recipient–year*. We focus on the 2010 to 2021 period because systematic project-level tracking by major multilateral development banks begins around 2010, and data coverage ends in 2021. We include 2009 because several predictors are lagged. The full population in that time period includes all recipient-years eligible to receive climate finance (1,952 observations), and our treated sample includes recipient-years that receive at least one project (1,338 observations). The sample is linked to 23 unique donor IOs and 13,349 unique multilateral climate finance projects.

estimators (PPML, negative binomial, and linear fixed-effects models), different operationalizations of donor network position, and a wide range of controls, including those capturing various recipient characteristics as well as additional donor features. We additionally show that there is no evidence that access to hubs and brokers differs across high-content and low-content climate projects, suggesting that access to these well-positioned IOs matters for general development assistance that may not be climate-focused, as well.

This project makes both theoretical and empirical contributions. Theoretically, we bridge work on international regime complexity with social network analysis (SNA). Although complex regimes are often implicitly or explicitly discussed as networks, SNA has rarely been applied to empirically uncover their structure (Green, 2022) and even less often to explain their effects. Our findings demonstrate the pay-off of importing SNA into the study of regime complexity by systematically showing that patterns of interaction among donors in the complex condition the ability of states to access a critical good: climate finance. This finding aligns with network scholarship in International Relations, showing that political networks have well-defined structural properties that shape the strategic environments in which states operate (Kinne, 2013; Scholz, Berardo and Kile, 2008; Cranmer, Desmarais and Kirkland, 2012; Kinne, 2018; Bellezza, 2025). It also extends this literature by demonstrating that these structural properties matter not only for overcoming cooperation and collective-action problems (the primary focus of extant literature) but also for shaping distributive outcomes.

Beyond simply serving as a testing ground for our theory, the issue of climate finance is substantively important. Climate finance needs are substantial and time-sensitive (Roberts and Weikmans, 2017; Roberts et al., 2021; Toetzke, Stünzi and Egli, 2022). A recent estimate suggests that, excluding China, developing countries will require $2.4 trillion annually by 2030 to meet their climate targets (Bhattacharya et al., 2023). Of this amount, the need for adaptation finance alone is projected at approximately $200 billion per year for the period 2021–2030 (UNEP, 2022). Thus, the question of how much CF gets channeled through IOs to developing countries remains a central aspect of international cooperation. Our findings suggest that in addition to which IOs dispense multilateral climate finance, how these IOs relate to one another and which states have access to well-connected IOs has important implications for who the system ends up benefiting. Policy proposals to enhance the effectiveness of climate finance, therefore, should pay attention to this dynamic network.

2 Applying Network Theory to Regime Complexity

We start with the premise that social network analysis (SNA) can advance our understanding of regime complexes by providing a toolkit for formalizing relational concepts and measuring them dynamically, while also linking them more explicitly to mechanisms of influence.

Regime complexity (RC) scholarship has long emphasized that the whole of a regime complex is greater than the sum of its parts (Alter and Meunier, 2009):[10] This animating work on how the macro-structure of the regime shapes governance outcomes. Specifically, the RC literature has elaborated concepts like "hierarchy," "density," and "fragmentation" to describe important relational properties of regimes characterized by a growing number of actors operating in the same issue area. This work has generated rich insights into questions about institutional authority, rule adoption, and cooperation and contestation (Eilstrup-Sangiovanni and Westerwinter, 2022; Biermann et al., 2009; Pratt, 2018). As representative examples, RC scholars have argued that lower levels of hierarchy in regime complexes produce more opportunities for forum shopping and confusion for actors, complicating accountability (Keohane and Victor, 2010; Orsini and Young, 2013; Eilstrup-Sangiovanni, 2021; Henning and Pratt, 2023; Widerberg and Pattberg, 2016). They have also proposed that higher levels of density may "stoke competition for authority and resources and reduce the propensity to cooperate" (Eilstrup-Sangiovanni and Westerwinter, 2022).

Social network analysis (SNA) can extend our understanding of the structures of regimes and the relations within by providing tools to capture features of regimes in a systematic, dynamic, and reproducible manner.[11] This

[10] "To think in terms of international regime complexity is to study interactive relationships and analyze how the whole shapes the pieces." p21.

[11] See Green (2022) for an exploration of hierarchy in the regime complex for Antarctic governance using SNA.

is important because, as acknowledged in Eilstrup-Sangiovanni and Westerwinter (2022, 248), "more fine-grained complexity measures may help to illuminate causes as well as effects of complexity," advancing our understanding of how complexes evolve over time and who benefits from that evolution.

From an SNA perspective, complexes are social structures composed of "nodes," or actors, connected by social ties of variable strength (Hafner-Burton, Kahler and Montgomery, 2009; Wasserman and Faust, 1994). At any given moment, patterns of ties between actors generate social structure, and as actors make and unmake connections, the social structure shifts accordingly. For example, macro-structural concepts like "hierarchy" can be captured using network centralization indices; "density" maps directly onto the proportion of realized ties among possible ones; and "fragmentation," often discussed by RC scholars in terms of overlapping mandates and governance diffused across multiple organizations, can be examined through measures of clustering that reveal how a network partitions into cohesive subgroups. Moreover, individual actors themselves may become more central or peripheral in the network as the macro-structure shifts. SNA thus provides measures of these topological features that vary as ties among actors form and break over time.

Beyond providing a systematic set of tools to measure both macro and local features of complex regimes, SNA can advance theory about how the dynamic structure of complexity impacts governance outcomes. A key insight of SNA is that, because actors are embedded in social structures, units of analysis (e.g., an IO-state dyad) are seldom independent.[12] Instead, social network theory expects that dyadic outcomes (e.g., whether an IO finances a state) will often be conditioned by extra-dyadic dependencies, i.e., by patterns of ties *beyond* the dyad. Otherwise put, networks do not just capture *existing* patterns of interaction; from a SNA perspective, they generate in-

[12]For notable edited volumes on the application of SNA to global governance, see Kahler (2009), Avant and Westerwinter (2016), and Seabrooke and Henriksen (2017).

formation that constrains or enables *future* interaction in predictable and well-theorized ways (Kinne, 2013; Hadden and Jasny, 2019; Hafner-Burton, Kahler and Montgomery, 2009).

For example, SNA has observed that actors with many connections – "hubs" – tend to attract a disproportionate share of new ties because each additional tie signals valuable information (e.g., about credibility, experience, status, etc.) thereby inviting still more connections. Network scholars call this tendency "preferential attachment," where newcomers attach to an existing node with a probability proportional to that node's current degree (Barabási and Albert, 1999). It has similarly been described as the tendency for "success to breed success" (Van de Rijt et al., 2014, 2016) and the Matthew effect, where "to everyone who has, more will be given" (Merton, 1968; Bol, De Vaan and Van De Rijt, 2018).

On this point, international relations scholars have found that the relative centrality of states in defense (Kinne, 2018) and police (Bellezza, 2025) cooperation networks generates information about credibility that predictably helps states overcome cooperation problems stemming from information asymmetries, thereby improving the odds of signing new agreements. Related research on transnational advocacy networks has shown that the adoption of issues by hub organizations like Human Rights Watch "confers not only visibility but also legitimacy to new issues" which then increases the odds that they will be adopted by other organizations (Carpenter, 2011, p. 76). The upshot from the SNA literature – that the centrality of some actors generates information that shapes the behavior of other actors – provides important insights for unpacking the dynamic nature of beneficiaries in complex regimes.

Building on this premise, we propose that SNA can help explain the *distributional effects* of regime complexes. Extant RC scholarship generates inconclusive expectations regarding the question of winners and losers. It clearly establishes that strong states appear advantaged under conditions of complexity: they can leverage their greater capacity to better navigate ambiguous obligations and exploit weak accountability (Alter and Meunier, 2009; Drezner, 2009), as well as bargain across multiple venues (Widerberg and Pattberg, 2016; Alter and Raustiala, 2018). Yet, some scholars examining complexes also point out that weaker states are not necessarily disadvantaged: a greater number of IOs provides more platforms to raise issues (Keohane and Victor, 2010) or find arenas better aligned with their preferences (Verdier, 2022).

SNA raises the possibility that the changing network position of IOs within a regime complex may confer (dis)advantages to states in their ability to access the resources those IOs provide. Because network positions shape the information actors receive, ties to well-positioned IOs may systematically advantage some states over others in securing regime benefits. Structural shifts within a complex may therefore shape not only whether actors comply with or challenge existing rules, but also who gains and loses materially from those shifts.

2.1 Networks, Information, and Distributional Outcomes

We argue that when states are connected to well-positioned IOs in regime complexes that allocate goods, such as aid, they plausibly gain informational advantages that translate into a competitive edge in securing those goods. We conceive of a well-positioned IO in two ways: the extent to which it is a "hub" or a "broker" in its social network. In what follows, we consider each in turn and, using the case of multilateral climate finance, illustrate why a state's access to a hub-IO and broker-IO might improve its chances of securing access to the regimes' key good (here, climate finance). We also theorize why the ability to capitalize on hubs and brokers may differ depending on recipient states' income-levels. Though we use multilateral climate finance to illustrate the informational pathways linking the network position of IOs to distributional outcomes for states, the theory should generalize to other domains characterized by complexity and information barriers to accessing the regimes' key benefits.

2.1.1 Advantages of Exposure to Hubs and Brokers

"Hubs" are actors who have more connections to other actors in a social system than their peers.[13] Such actors are the most active, and thus visible, in their social networks (Borgatti, 2005), and tend to be "recognized by others as major channels of relational information; indeed, a crucial cog in the network" (Wasserman and Faust, 1994, 179). This privileged access means that hubs often learn about important information earlier than others and can filter and disseminate it more widely, serving as both a *signal* to peers and a *channel* that transmits information.

Connections within a network can provide informational advantages both to specific IOs and to states that are well-connected to these IOs. For instance, when IOs collaborate by co-financing projects, they share operational knowledge: co-financiers learn each other's priorities, templates, and procedures.[14] In turn, this knowledge shared by connected IOs may be passed on to states that rely on those IOs. In the climate finance world, a borrower connected to an IO that is central to multilateral climate finance can learn more about the types of financing available, the kinds of requirements different IOs have, and how to assemble projects that will be attractive to funders. The Global Environment Facility (GEF), for instance, has noted that "knowledge is often generated during project implementation and facilitates the achievement of environmental benefits primarily through monitoring systems, information sharing, and awareness raising" (GEF Independent Evaluation Office, 2017). In other words, IOs that work together share knowledge, and being

[13]We are referring here to "degree centrality," formally defined as the quantity of nodes to which each node is adjacent.

[14]Our emphasis on inter-organizational learning via prject level co-financing is different from Clark (2025) emphasis on the collective action problems that arise through such pooling money and expertise across IOs.

connected to a hub-IO in the climate finance world may boost a recipients' knowledge about the types of financing available, the kind of requirements different IOs have, and how to put together project proposals that will be attractive to funders. In domains that require specialized knowledge, these knowledge spillovers can be valuable.

Additionally, a recipient's track record with a well-connected IO can signal to other donors that a recipient is capable of managing complex projects. Donors are often concerned about whether recipients can meet technical standards, comply with monitoring requirements, and deliver results (Hoeffler and Outram, 2011). While creditworthiness in global finance is typically assessed through sovereign bond ratings, some domains, like climate finance, target countries that typically lack access to capital markets (World Bank, 2023). In this context, a connection to a hub IO may serve as an alternative signal: if a recipient has already been vetted and funded by a well-connected IO, others may infer that it possesses the necessary expertise and capacity to implement similar projects. In sum, we propose that hub IOs may improve both the information a recipient receives (about other donors) *and* the signals it sends (about its credibility to other donors). Hence, we hypothesize that:

H1: States with greater exposure to hub IOs at time $t-1$ *will receive more new projects at time* t*, all else equal.*

Whereas hubs connect recipients to many other donors, brokers connect recipients to otherwise disconnected parts of the donor network. Brokers occupy what social network analysis (SNA) calls "structural holes," positions that allow them to facilitate the flow of information between siloed groups that would not otherwise interact (Burt, 1992). These silos correspond to what SNA terms *clusters*: cohesive groups of actors that interact much more frequently with one another than with others in the system and, in doing so, may converge on shared standards and practices. Classic sociological studies show that brokers can benefit by arbitraging ideas and practices that circulate within otherwise isolated groups, a mechanism Burt (2005) describes as the "information and control benefits" of brokerage. In organizational research, for example, managers who straddle departmental or professional boundaries are often positioned to identify opportunities, recombine practices, and innovate more quickly than their peers (Uzzi, 1997; Obstfeld, 2005). In global governance, Seabrooke and Henriksen (2017) similarly show how transnational professionals leverage brokerage positions to translate expertise across domains and shape how issues are framed and governed, often influencing which solutions appear legitimate and which actors are recognized as competent.

While classic accounts of brokerage emphasize actors that bridge structural holes through sparse, non-redundant ties (Burt, 1992), our theoretical interest lies in a distinct but related form of brokerage: positions created through sustained, repeated collaboration across otherwise weakly connected groups. In the context of multilateral co-financing, information about project design, implementation standards, and recipient performance is more likely to be generated and transmitted through repeated joint work than through one-off relationships. We therefore focus on *embedded brokerage*, where organizations occupy intermediary positions between donor communities while remaining deeply involved in ongoing collaborative relationships. Section 3.3.2 formalizes this distinction empirically by contrasting embedded brokerage with brokerage defined purely by structural position. We expect:

H2: States with greater exposure to embedded broker IOs at time $t-1$ *will receive more new projects at time* t*, all else equal.*

2.1.2 Poorer versus Wealthier Developing Countries

While ties to hubs and brokers provide recipients with informational and signaling advantages, their effects are likely to vary systematically across income groups. The direction of this heterogeneity is not self-evident. Poorer states may benefit more because network ties expose them to widely diffused practices and enhance their credibility with other donors. At the same time, wealthier states may be better positioned to capitalize on these connections because they have a greater capacity to process and act on complex information flows.

Hub ties illustrate this ambiguity. On one hand, connecting to central donors can provide poorer states with access to information and practices that would otherwise be out of reach, as well as confer reputational benefits that bolster their standing with the broader donor community. On the other hand, the very breadth of these connections could possibly create coordination challenges. Recipients must reconcile overlapping rules, manage diverse procedures, and coordinate among multiple powerful donors. As regime complexity scholars emphasize, "master[ing] the relationship among rules and institutions within a regime complex takes substantial knowledge and capacity on the part of the relevant actors—a feature that arguably favors larger and wealthier actors" (Alter and Raustiala, 2018, 338). Wealthier states may thus be better equipped to absorb the thick information flows that hub ties generate.

A similar ambiguity applies to brokerage ties. Brokers connect otherwise siloed clusters of donors, channeling recipients toward specialized resources. For poorer states, such connections can be especially valuable, compensating for limited capacity to navigate diverse donors independently. Yet brokerage ties also impose coordination burdens, as recipients must engage with varied technical standards, reporting requirements, and institutional procedures, all of which place a heavy burden on bureaucratic capacity. Wealthier states, with stronger administrative infrastructures, may be better able to manage these challenges and to translate brokerage ties into new projects.

Despite these competing logics, our emphasis on information as the key mechanism leads us to expect that lower-capacity actors benefit more from both hub and broker ties. Access to a hub and a broker should simplify and clarify the cacophony of information in the complex, and the marginal (additive) value of that knowledge should be higher for poorer states. With connections to hubs and brokers, poorer developing countries are both more likely to be exposed to more new information than their wealthier, middle-income counterparts, and the clarifying role of that information should be higher for these poorer countries. A similar point applies to signaling. Wealthier developing countries have typically already established multiple channels for disseminating information about their creditworthiness, priorities, and institutional capacities. Many access private capital markets, thereby making their creditworthiness widely known, and engage with international organizations through non-climate projects, making them familiar actors within donor networks. As a result, the positive signal generated when a recipient is funded by a hub IO is likely to be less consequential for these states. The converse holds for lower-income countries: connections to central actors in the network can provide novel platforms for making their projects and implementation capacity visible to a broader donor audience. We thus expect:

*H3 (Hub * Wealth): The effect of hub exposure on subsequent project counts will be stronger for poorer developing country recipients.*

*H4 (Broker * Wealth): The effect of broker exposure on subsequent project counts will be stronger for poorer developing country recipients.*

Overall, our hypotheses suggest that recipients' access to well-connected IOs, i.e., those that collaborate (via co-financing) frequently in the multilateral climate finance complex, should matter significantly for their receipt of climate finance. Notably, and perhaps counterintuitively, this perspective brings a new focus to the IO's importance, suggesting that it is not just based on measures of its capacity or size, but also on its position within a changing network of interacting IOs.

3 Research Design

3.1 The Case

As already discussed, we explore our theoretical intuitions using the case of multilateral climate finance, and our data (2010-2021) on multilateral climate finance are drawn from the OECD, which follows the multilateral development banks' (MDBs') common framework in deciding the climate finance contribution of each project (see Section 1). Since 2011, MDBs have been releasing joint reports on climate finance based on shared guidelines. The OECD, in turn, integrates these collective guidelines from the MDBs to identify projects with expected benefits toward addressing climate change and to verify the project's purported contributions to climate change, marking projects with no identifiable value as zero.[15]

Multilateral climate finance is important in its own right, as it constitutes a critical dimension of international cooperation. During the UNFCCC's 2009 Copenhagen climate summit (COP15), developed countries pledged to mobilize $100 billion annually by 2020 for less wealthy nations—a figure that has since drawn considerable scrutiny and debate (Roberts et al., 2021; Michaelowa and Michaelowa, 2011). Despite the controversy, CF has been a pillar of UNFCCC negotiations, with Copenhagen's pledge to provide "scaled up, new and additional, predictable and adequate funding" to developing countries (United Nations, 2010). The 2015 Paris Agreement further elevated the prominence of CF in global climate governance by calling for increased flows, particularly highlighting the role of IOs in channeling these funds (Agreement, 2015).[16] More recently, in November 2024, as part of the

[15]Our close examination of the OECD, however, revealed that World Bank co-financing was not adequately captured in the OECD data. To rectify this issue, we used all project finance data reported by the Bank and integrated the projects' co-financing information into the OECD dataset.

[16]Some of the nationally determined contributions (NDCs) under Paris remain contingent on the receipt of adequate international climate finance, as without these funds,

implementation of Paris, parties established a new annual climate finance target of $300 billion by 2035. This New Collective Quantified Goal replaces the earlier $100 billion commitment and underscores the continuing importance of international CF. In this context, international organizations are once again expected to increase their climate finance and be critical conduits for these funds (Kaya and Leblebicioglu, 2025).

Meanwhile, evidence suggests that developing countries do not find it easy to navigate the complex landscape of multilateral climate finance (Least Developed Countries (LDC) Group, 2024). In particular, the demands of the "project cycle"—from formulating an idea for financing by IOs to completing a project—further heighten the importance of information, particularly about requirements and how to meet them. In one example, the Green Climate Fund has a range of typical prerequisites, including feasibility studies, environmental and financial models, and gender analyses. Furthermore, such requirements vary across IOs, compounding the challenges that recipients, particularly poorer ones, face. These stipulations imposed by the financiers help explain why developing countries, particularly the least developed among them, have repeatedly raised concerns about the accessibility of climate finance (ibid). The more demanding the requirements become, the more difficult it becomes for lower-capacity actors to access and manage the system, increasing the importance of information for effective participation. However, having clear, quality information, in the first place, may require the right type of connections.

In this context, understanding how changing relationships among IOs impacts the distribution of climate finance remains an important question for global climate policy. Specifically, we primarily seek to answer whether and when distributive outcomes differ for recipients funded by IOs that are well-connected in the multilateral climate finance network compared to those

the developing countries cannot achieve the mitigation and adaptation targets outlined in these NDCs (Overholt et al., 2024).

that are funded by more isolated IOs. Additionally, we explore whether these effects differ for more versus less well-off developing countries.

3.2 Dependent Variable

Our dependent variable is the count of multilateral climate finance projects that each recipient country receives in year t. We draw these counts from the OECD's Official Development Assistance (ODA) data, which separately tracks climate-related development assistance from multilateral institutions at the *project-level*.[17] We focus on *project counts* rather than commitment values because the data do not permit the precise determination of the climate-related commitment value of a project. Since a project can serve multiple objectives simultaneously, without knowing the exact contribution to climate goals (i.e. the precise amount qualifying as climate finance), using commitment values runs the risk of exaggerating the project's contribution to climate goals. In addition to project counts, we also make use of the OECD's marking of the climate component of the project, which ranges from principal to significant to "climate components" in descending order to identify the project's contribution to addressing climate change. Table A.1 in the Appendix provides examples of different types of climate-related projects in the database.

Across the period examined in our analysis (2010-2021), 13,756 unique multilateral climate projects were approved for 145 recipient countries. As shown in Figure 3.1, the total number of climate finance projects has increased significantly over time, particularly after the 2015 Paris Agreement. The typical country-year received 8 projects (median), three-quarters of country-years received fewer than 15, and nearly one-third of country-years received 3 or fewer projects. Most of the projects are marked as having "climate components" (about 65%), meaning they combine climate goals with

[17]Development assistance, by definition, means that a quarter of the financing provided in any given project comes in the form of grants.

other types of development objectives (Figure 3.1 C)[18] and were marked as contributing to *both* mitigation and adaptation (82%) (Figure 3.1 B).[19] Moreover, climate finance projects have been relatively evenly distributed throughout the developing world (Figure 3.2). The top ten recipient countries account for only 21% of all recipient–project observations, and 145 countries received at least one project between 2010 and 2021.

[18]This is in keeping with (Kaya and Leblebicioğlu, 2024), which finds that most of the World Bank's climate finance projects, even after the Paris Agreement, are "mixed" projects that combine climate objectives with other goals.

[19]Because most projects are marked as contributing to mitigation and adaptation goals, the separation of mitigation and adaptation finance in this analysis does not make sense.

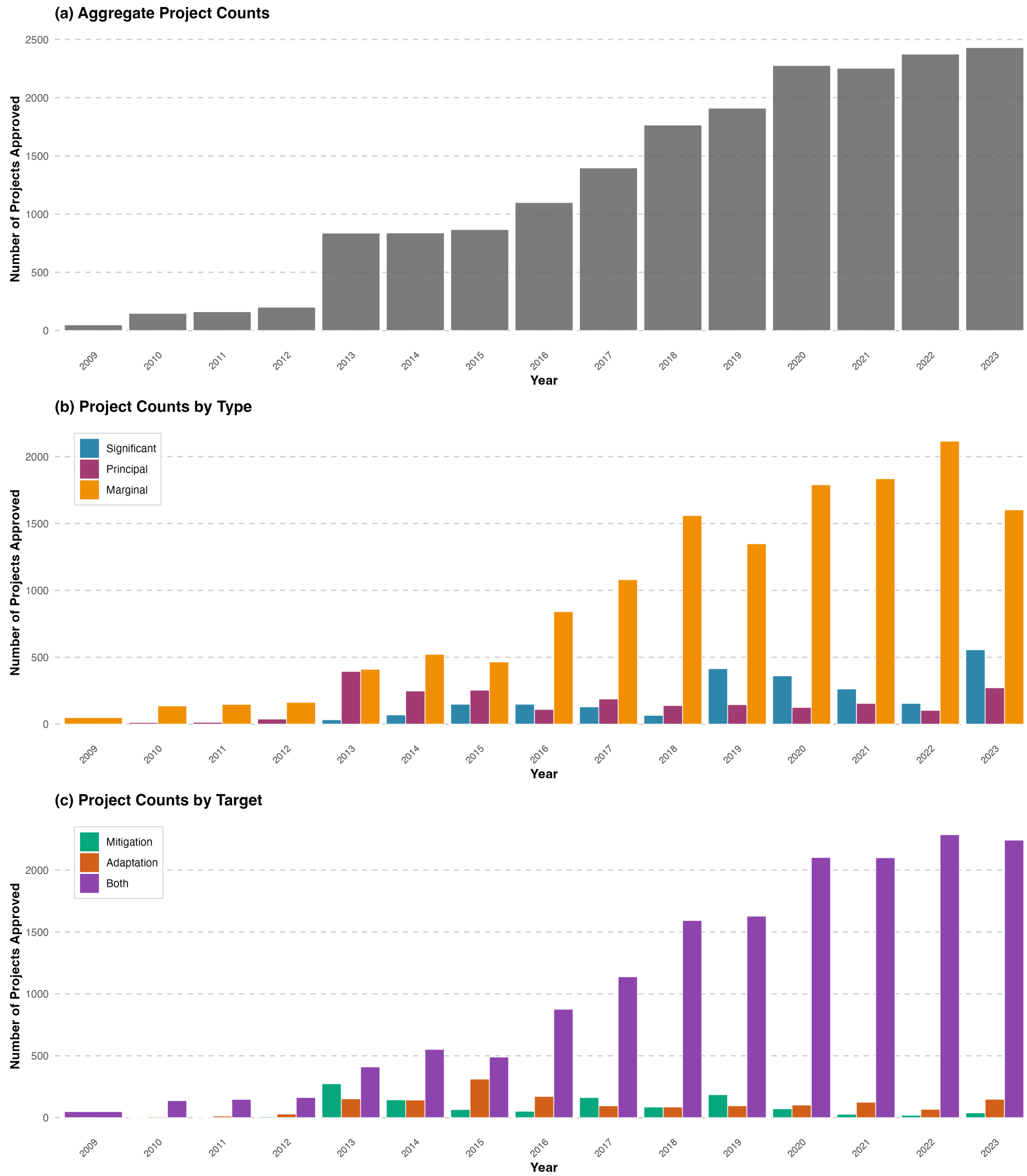


Figure 3.1: Multilateral Climate Projects Approved

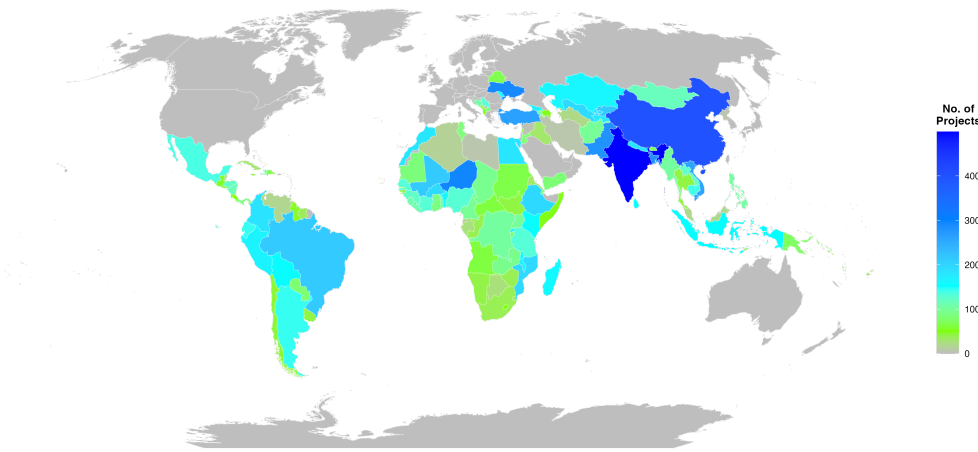


Figure 3.2: Distribution of Projects by Recipient, 2010-2021

Note: The top ten recipients of projects are India (499), China (400), Niger (295), Ukraine (291), Bangladesh (282), Pakistan (279), Turkey (263), Vietnam (257), Kyrgyzstan (214), and Brazil (213). Together, these countries account for approximately 21% of all recipient–project observations during the period.

3.3 Network Predictors

We construct our key predictors – exposure to hub and broker IOs – by (i) mapping the multilateral climate finance network, (ii) identifying the relative positions of IOs within that network, and (iii) constructing variables that capture recipients' exposure to these variably positioned IOs. The following sections explain each of these steps.

3.3.1 Step 1: Mapping the Network

To construct the multilateral climate finance network, we define the "nodes" in the complex as international organizations involved in providing climate finance.[20] A connection or "tie" between IOs forms when they co-finance discrete climate projects. As noted previously (Section 1), co-financing ties capture a concrete actualized relationship. The strength of each tie (i.e., each co-financing relationship) in the network is dependent on the prevalence of co-financing within each IO dyad. That is, a tie becomes stronger when two IOs co-finance more projects.

Empirically, co-financing has become increasingly common in multilateral climate finance. In 2009, no approved projects involved more than one donor within a given year, but by 2023, nearly one in five projects (18.6%) were co-financed. Since co-financing began in 2010,[21] co-financed projects account for 2,793 approved projects spanning 142 recipient countries. Today, nearly all IOs active in multilateral climate finance (95.5%) have participated in co-financing at least once, led by the GEF, which has co-financed more projects than any other donor.

Substantively (as proposed in Section 2.1), co-financing represents a key channel for the transmission of information between IOs within the regime complex. Thus, an IOs co-financing ties have potential implications for how

[20] In our analysis, this includes the 23 IOs listed in Appendix Table A.2

[21] No project that appears before 2010 in the OECD multilateral climate finance data ever involved more than one donor (within-year or at any point in its lifetime).

much valuable information it has to pass on to the states it finances. By mapping the evolving web of co-financing ties, we trace how the structure of this horizontal (IO to IO) information flow has changed over time. As IOs form new partnerships or end existing ones, the topology of the donor network shifts, altering both the positions of individual IOs and the overall architecture of the regime complex, with implications for how information circulates.

Figure 3.3 illustrates these dynamics by depicting the annual co-financing network of IOs over time. The figure shows that the network is neither static nor uniform: the extent of collaboration, the prominence of particular IOs, and the overall pattern of interconnection vary from year to year. To summarize these shifts, we report two standard network-level descriptors—centralization and density—which provide compact descriptions of overall concentration[22] and overall connectedness.[23] While these network-wide properties describe how collaboration is organized in a given year, they do not capture how individual IOs are positioned within the regime complex. We therefore turn next to identifying hub and broker IOs.

[22] Formally, we measure centralization using Freeman's degree centralization index (Freeman, 1979), which captures the extent to which co-financing activity is concentrated around dominant IOs versus distributed more evenly across participants. The index ranges from 0 (perfect equality) to 1 (maximum concentration), with higher values indicating a more hierarchical donor network.

[23] Formally, network density is calculated as the ratio of observed co-financing ties to the total number of possible ties among IOs. It ranges from 0 (no co-financing ties) to 1 (every possible IO pair co-finances at least once).

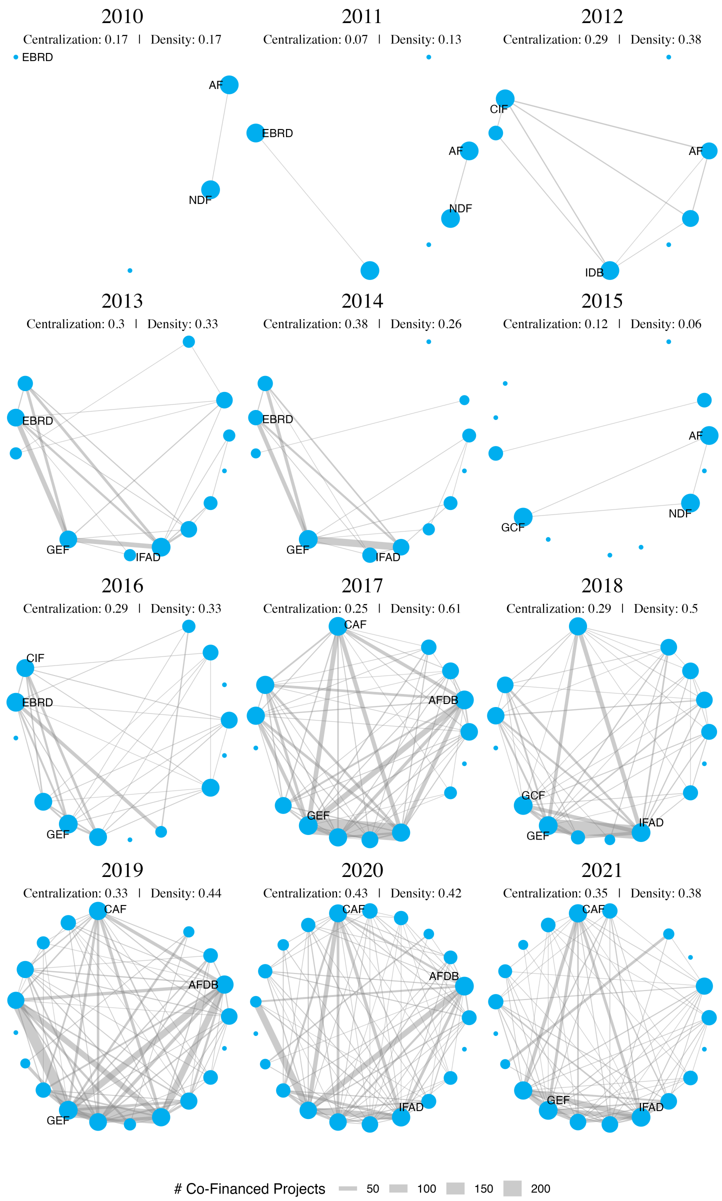


Figure 3.3: Multilateral Climate Co-Financing Network

Note: Each panel shows the annual network of IOs that financed at least one climate project in the given year. Nodes represent IOs; edges connect IOs that co-financed the same project, with edge thickness proportional to the number of shared projects; and node size reflects degree centrality (number of distinct co-financing partners). Positions are fixed across panels so that each IO appears in the same location over time. Labels highlight most central IOs in a given year by degree centrality (No. of ties). Some IOs appear without edges (isolates) because they did not co-finance any individual project with another IO in that year. Reported network statistics (density and centralization) summarize the overall structure of collaboration in each year.

3.3.2 Step 2: Network Position of IOs

In addition to changes in the global structural properties of the co-financing network, individual IOs may become more or less central within the network over time. Importantly, centrality in a co-financing network can take different forms. Some IOs become centrally positioned because they collaborate widely or intensively with other donors, accumulating experience through repeated joint project work. We refer to these organizations as **hubs**. Other IOs become central because they occupy positions between otherwise weakly connected parts of the network, gaining exposure to distinct donor communities and practices. We refer to these organizations as **brokers**. Although these roles may overlap, they are conceptually distinct and need not coincide: hubs derive informational advantages from their frequency of collaboration, whereas brokers derive these benefits from their position at the intersection of different donor groups.

We operationalize hubness based on the frequency of co-financing activity. An IO is considered a hub if it participates in a large number of co-financed projects, whether by working with many different partners or by collaborating repeatedly with the same partners. Empirically, we capture this idea using *weighted degree centrality*, which measures the total number of projects an IO collaborates on across all of its co-financing relationships.

We operationalize brokerage based on sustained exposure to otherwise weakly connected parts of the donor network. To capture this form of brokerage, we use *weighted betweenness centrality*. Because betweenness is weighted by repeated co-financing activity, IOs score highly on this measure only when they are consistently embedded in dense collaborative ties that connect otherwise weakly connected groups. We refer to these organizations as *embedded brokers*. In this measure, ties involving more shared projects are treated as closer connections, reflecting the idea that information flows more readily through repeated collaboration than through one-off partnerships.

As a robustness check on the measurement strategy, we alternatively operationalize brokerage using *unweighted* betweenness centrality, which captures brokerage in a purely structural sense by identifying IOs that lie on many shortest paths between other IOs, irrespective of collaboration intensity. We refer to this alternative measure as *structural brokerage*. In contrast to embedded brokerage, this alternative measure is not positively associated with subsequent project receipt (see Appendix Table A.17), consistent with the idea that information transmission is more likely to occur through repeated collaboration than through one-off connections.

Figure 3.4 illustrates these measurement distinctions using the 2020 co-financing network, highlighting the difference between high-frequency **hubs**, **embedded brokers** that connect distinct donor communities through repeated collaboration, and **structural brokers** whose bridging roles are not necessarily embedded in sustained co-financing relationships. That year, the Global Environment Facility and the African Development Bank (AfDB) emerged as embedded brokers, combining both high co-financing frequency and thick cross-community ties. For example, GEF participated in nearly 400 co-financed projects in 2020, while AfDB participated in over 200. In the network, both organizations occupy positions at the boundary between donor communities and maintain multiple high-intensity co-financing relationships on either side of those boundaries, reflecting sustained collaboration across otherwise weakly connected clusters. The figure also highlights the presence of *structural brokers*, most notably the Inter-American Development Bank (IDB). Although the IDB occupies an intermediary position between donor communities, its bridging ties are comparatively thin, typically involving only one or a small number of shared projects with each partner.

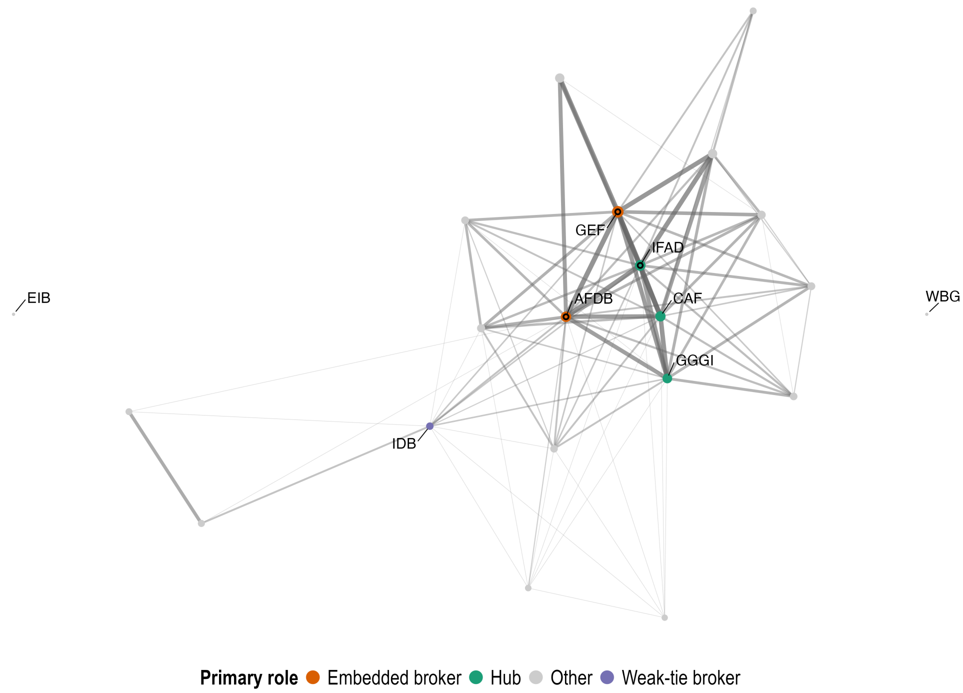


Figure 3.4: Hubs and Brokers in the 2020 Multilateral Co-financing Network

Note: The figure shows the 2020 co-financing network, where nodes represent IOs and ties indicate shared projects. Tie thickness reflects the number of co-financed projects. Node color denotes an organization's primary role: hubs (top 25th percentile of weighted degree), embedded brokers (top 25th percentile of weighted betweenness), structural brokers (top 25th percentile of unweighted betweenness), and other donors.

3.3.3 Step 3: Recipient Exposure Metrics

Our key predictors capture the extent to which recipient states are exposed to hubs and (embedded) brokers. We measure these recipient exposure metrics as follows:

$hub\_exposure_{i,t-1}$ measures how many of recipient i's donors at time $t-1$ are network hubs. A hub is defined as a donor whose *weighted degree centrality* is at or above the 75th percentile of the annual donor co-financing network.[24] Weighted degree centrality captures the total frequency of a donor's co-financing activity by summing the number of projects shared across all of its co-financing ties. Donors that co-finance many projects, whether with many partners or repeatedly with the same partners, score higher on this measure, reflecting their role as high-volume collaborators.

$broker\_exposure_{i,t-1}$ measures how many of recipient i's donors at time $t-1$ are network brokers. A broker is defined as a donor whose *weighted betweenness centrality* is at or above the 75th percentile of the donor network. Weighted betweenness centrality identifies donors that are repeatedly involved in dense co-financing relationships that connect otherwise weakly connected parts of the donor network. To capture this logic, path length is computed using weighted distances rather than edge counts: each edge's length is defined as the inverse of the number of shared projects (1/project count), so donors with many shared projects are treated as closer collaborators. Donors that occupy a large number of these weighted shortest paths score higher on weighted betweenness, reflecting their sustained involvement in co-financing relationships across different donor groups.

Our data suggest that recipients have limited exposure to hub and broker IOs. Conditional on project receipt, the median recipient is connected to one hub and one broker, and three-quarters are connected to one or fewer of each.[25] In the upper tail, however, some recipients are connected to as many as four hubs and four brokers.

[24]Percentile thresholds are computed over all donor organizations with any climate-finance activity in a given year, including donors that do not co-finance in that year (i.e., isolates with zero weighted degree). However, because hub status is assigned only to donors whose weighted degree is *greater* than the annual 75th percentile threshold, donors with zero co-financing activity in a given year are never classified as hubs or brokers, even in early years when co-financing is sparse.

[25]Appendix Table A.4.

We conclude this section by clarifying several aspects of how the recipient exposure measures are constructed. Our decision to rely on threshold-based hub and broker measures in the main models reflects both theoretical and practical considerations. Substantively, our argument centers on recipient exposure to particularly well-connected donors—those located in the upper tail of the co-financing network and thus likely to possess disproportionate informational advantages. A percentile-based threshold is well suited to capturing this nonlinearity. From a practical standpoint, these indicators are easier to interpret than continuous exposure measures and are also less sensitive to extreme values in the highly skewed distribution of donor centrality.

However, we also undertake robustness checks using alternative measures of centrality. Specifically, we construct continuous exposure measures that do not rely on percentile cutoffs by computing *average donor degree*, defined as the average weighted degree centrality of all donors financing recipient i in year $t-1$, and *average donor betweenness*, defined as the average weighted betweenness centrality of recipient i's donors in year $t-1$. These measures capture overall donor embeddedness in the co-financing network rather than exposure to donors occupying particularly central or bridging positions. Moreover, as a placebo-style check on our exposure measures, we also redefine recipient exposure based on donors located in the *bottom* 25% of the donor co-financing network rather than the upper tail.

A related concern with exposure measures constructed from co-financing networks could be endogeneity arising from correlation between recipient project activity and donor network position. Because IO–IO ties form when donors co-finance the same projects, a large multi-donor project for a given recipient in year $t-1$ could, in principle, both expand that recipient's donor portfolio and contribute to donors' centrality in the network. If so, a recipient might appear to be exposed to hubs or brokers partly because its own projects helped make its donors appear central, rather than because it was connected to donors that were already well embedded in the broader co-financing system. In short, the concern is that we may be explaining our outcome using a regressor that partially reflects the outcome-generating process itself.

Several features of the research design mitigate this concern. Donor centrality is computed at the global IO–year level based on thousands of co-financed projects across roughly 140 recipient countries, so any single recipient's projects contribute only minimally to a donor's overall network position and are unlikely to shift donors into or out of the top quartile of centrality. In addition, all models condition on lagged measures of recipient's prior project portfolio breadth (donor count) and size (commitment amount), as described in the next section.

3.4 Controls

Our control strategy accounts for non-network factors that may influence the allocation of multilateral climate-finance projects. We group these controls into three categories: recipient need and capacity, recipient integration and path dependence within the climate-finance system, and donor attributes. All controls are lagged by one year.

First, countries that are more vulnerable to climate risks, as well as those with larger greenhouse gas emissions, may be more likely to seek and receive climate-finance projects, regardless of network structure. We thus include the ND_GAIN Country Index, an aggregate measure of climate vulnerability that captures countries' exposure to climate risks and their capacity to adapt to these effects. We additionally include the country's annual CO_2 emissions; the pressure to mitigate is likely to increase with higher emissions. We also control for logged GDP per capita and logged population, as poorer and more populous states tend to receive more development assistance (Kilby, 2024), which might also apply to the case of climate finance. In addition, political and institutional characteristics of recipients may shape donors willingness to lend to them, as is widely recognized in the aid literature. We, therefore, include a measure of democratic governance, the V-Dem Polyarchy Index, to account for the possibility that donors favor democratic institutions.[26] Finally, because strategically important states may receive preferential treatment, we include an indicator for temporary United Nations Security Council (UNSC) membership, following evidence that UNSC members receive greater allocations from major global economic institutions like the World Bank (Vreeland and Dreher, 2014).

Second, project allocation may exhibit path dependence, as recipients that are already well integrated into the climate-finance system may continue to attract projects. To account for this dynamic, we control for the (log) total amount of climate-related finance committed to the recipient in the previous year[27] along with the number of distinct donors financing the recipient in the previous year, which proxies for the breadth and size of the recipient's existing project portfolio.

Finally, we control for recipients' exposure to high-capacity donors. Some recipients may receive more projects, not because their donors occupy advantageous network positions, but because they are funded by donor organizations with a greater capacity to lend. To account for this possibility, we construct a recipient-level measure of donor capacity that captures the average size of the climate-finance portfolios of the donor organizations funding each recipient in the previous year. By including this measure, we interpret the estimated effect of exposure to hubs and brokers net of their underlying capacity to supply climate finance. Appendix Table A.4 includes the summary statistics, and Appendix Table A.3 provides the codebook.

[26]Democracies tend to have more robust climate policy (Bättig and Bernauer, 2009).

[27]While commitment amounts are not reliable at the project level, this aggregate measure serves well as a control.

3.5 The Model

Our outcome of interest is the number of climate finance projects a recipient country receives in a given year. Our key predictors capture how exposed each recipient is to well-positioned international organizations in the multilateral co-financing network, specifically to IOs that occupy hub or broker positions in the previous year. Conceptually, project allocation involves two linked processes: (1) whether a country receives any climate finance in a given year (the extensive margin), and (2) how many projects it receives conditional on receiving at least one (the intensive margin).

A key threat to causal inference is that unobserved characteristics may affect both margins. Specifically, factors that increase the probability that a country receives at least one project in year t may be correlated with factors that affect how many projects it receives conditional on positive participation. If such factors are unobserved, standard count models would yield biased estimates of network effects, conflating true network advantages with these correlated unobservables.

To address such potential selection bias, we employ a two-stage selection correction approach. The first stage uses a probit model to estimate the probability that country i receives at least one climate-finance project in year t. The second stage models the count of projects received conditional on selection in year t. The second stage includes the Inverse Mills Ratio (IMR) derived from the first stage to adjust for the correlation between unobserved factors affecting annual participation and those affecting project intensity.

Importantly, we model *annual participation* rather than one-time entry into the climate finance system. This reflects the institutional reality that project approval occurs through repeated annual decisions, and countries must compete for funding each year, regardless of their prior history. Our data confirm this pattern: among the 143 countries that received projects at least once, the median country participated in only 69% of its eligible years. Moreover, dropout is common: 45% of participating countries experienced at least one year with zero projects after receiving their first project.

For the selection equation, we define the population of potential recipients as non-high-income countries using the World Bank's income classification.[28] This yields a population of 158 treatment-eligible states observed annually from 2010 to 2021, generating 1,988 country-year observations. For the outcome equation, the population is restricted to the 1,338 country-years in which at least one climate finance project was received.

Our two-stage approach requires an instrument that affects the probability of annual participation but does not influence project counts conditional on participation. We use political alignment with the United States, measured by United Nations General Assembly (UNGA) ideal-point distance from the U.S. (Bailey, Strezhnev and Voeten, 2017). A large literature supports the relevance of political alignment with major shareholders for access to multilateral finance (Thacker, 1999; Barro and Lee, 2005; Andersen, Hansen and Markussen, 2006; Stone, 2004; Dreher and Jensen, 2007; Stone, 2008; Kilby, 2013; Vreeland, 2019). At the same time, recent work finds that political alignment does not affect the number of climate projects that countries receive (Kaya and Leblebicioglu, 2025).

Diagnostic tests support the plausibility of this instrument (Appendix A.2). In the first-stage probit selection equation, UNGA ideal-point distance significantly predicts entry into the climate-finance system: a one-unit increase in distance from the United States reduces the probability of receiving any climate-finance project by approximately 3.5 percentage points on average (AME $= -0.035$, $p < 0.05$). When political alignment is included directly in the outcome equation estimated on the selected sample, it does not significantly predict the number of projects a country receives once it has entered the system ($\beta = -2.0$, $p > 0.10$). This pattern is consistent with the exclusion restriction.

[28] We nonetheless include 18 high-income countries that have received climate-finance projects. See Appendix Table **??** for a list of these exceptions.

Formally, the model consists of two equations. The selection equation is:

$$S_{it} = \alpha_0 + \alpha_1 Z_{i,t-1} + \boldsymbol{\theta}^\top \mathbf{W}_{i,t-1} + \tau_t^S + u_{it}, \tag{1}$$

where S_{it} equals 1 if country i received at least one project in year t and 0 otherwise. $Z_{i,t-1}$ is the instrument (UNGA ideal-point distance from the U.S.), $\mathbf{W}_{i,t-1}$ is a vector of covariates influencing selection, and τ_t^S are year fixed effects.[29] Equation (1) is estimated via probit on the eligible country population.[30] From the fitted values, we compute the *Inverse Mills Ratio* ($\widehat{\text{IMR}}_{it}$) for each observation.

Conditional on selection ($S_{it} = 1$), the outcome equation is:

$$Y_{it} = \beta_0 + \beta_1 \text{Network}_{i,t-1} + \boldsymbol{\gamma}^\top \mathbf{X}_{i,t-1} + C_i^Y + \tau_t + \lambda \widehat{\text{IMR}}_{it} + \epsilon_{it}, \tag{2}$$

where Y_{it} denotes the number of climate-finance projects received by country i in year t. The term $\widehat{\text{IMR}}_{it}$ is the inverse Mills ratio obtained from the first-stage probit selection equation and controls for non-random selection into the climate-finance system. $\text{Network}_{i,t-1}$ denotes the network variable of interest (e.g., hub exposure, broker exposure, or interactions with recipient characteristics), and $\mathbf{X}_{i,t-1}$ is a vector of lagged control variables. C_i^Y and τ_t denote country and year fixed effects, respectively. Standard errors are clustered by country in all specifications to account for serial correlation within panels.

Our preferred specification uses negative binomial regression, which is best suited to accommodate the substantial overdispersion in our count outcome.[31] To demonstrate robustness to this modeling choice, we also report

[29]Country fixed effects are omitted from the selection equation due to limited within-country variation in the annual selection indicator, which leads to separation in a fixed-effects probit model.

[30]Variables related to prior project receipt are excluded from the selection equation and instead modeled in the outcome stage.

[31]The variance-to-mean ratio in the outcome stage is 14.3, exceeding the equidispersion assumption of standard Poisson models.

results using Poisson pseudo-maximum likelihood (PPML) and OLS.

4 Results

Our core specifications correspond to our hypotheses. Models 1 and 2 examine the direct effects of recipient exposure to hubs and brokers, respectively. Model 3 interacts hub exposure with GDP per capita to assess whether poorer countries derive differential access to projects from hub exposure. Model 4 does the same for broker exposure.

Table 4.1 reports our primary results based on Equation (2). In the first baseline specification (Column 1), exposure to hub donors is positively and statistically significantly associated with subsequent project receipt. Because the model conditions on the total number of donors a recipient has in the previous year, the coefficient on hub exposure should be interpreted as a compositional effect: holding the size of a recipient's donor portfolio constant, replacing a non-hub donor with a hub donor is associated with a 10.3 percent increase in the number of projects received.

In the second baseline specification (Column 2), exposure to broker donors is also positively and significantly associated with subsequent project receipt. As in the hub specification, the model conditions on the total number of donors, so the coefficient on broker exposure captures a compositional effect. Holding the size of a recipient's donor portfolio constant, replacing a non-broker donor with a broker donor is associated with an approximately 8 percent increase in the expected number of projects received.

We next examine whether these network advantages vary systematically with recipient income. In the interaction models (Columns 3 and 4), income is measured continuously using logged GDP per capita, allowing the effects of access to hubs and brokers to vary as recipients experience changes in their level of economic development over time. The results show that exposure to hub and broker donors is strongly associated with increased project allocations when recipients are poorer, with the marginal effect declining as a recipient's income rises. As shown in Figure 4.1, predicted project counts

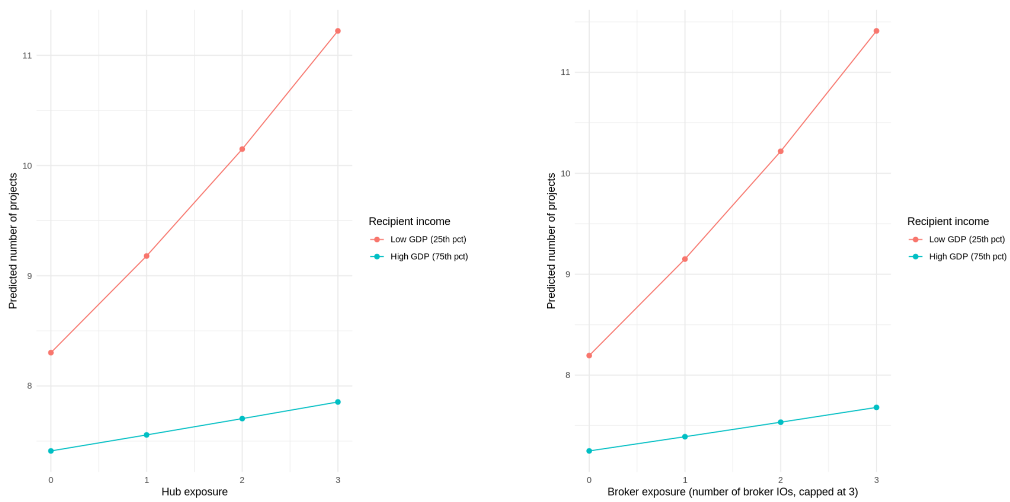
Table 4.1: Main Results, Negative Binomial

	(1)	(2)	(3)	(4)
Dependent variable: Annual project count				
ND-GAIN index	−0.0072	−0.0085	−0.0103	−0.0106
	(0.0153)	(0.0156)	(0.0149)	(0.0152)
CO_2 emissions (log)	−0.0200	−0.0214	−0.0226	−0.0246
	(0.0214)	(0.0223)	(0.0215)	(0.0217)
Log population	1.669***	1.786***	1.490***	1.633***
	(0.368)	(0.374)	(0.367)	(0.373)
Log GDP per capita	0.2309$^{\cdot}$	0.2297$^{\cdot}$	0.2670*	0.2630*
	(0.126)	(0.126)	(0.126)	(0.126)
UNSC member	−0.0039	0.0035	−0.0220	−0.0126
	(0.0729)	(0.0694)	(0.0745)	(0.0703)
V-Dem Polyarchy	−0.0874	−0.0130	−0.1419	−0.0443
	(0.253)	(0.252)	(0.249)	(0.248)
Log commitment amount	0.2123***	0.2100***	0.2128***	0.2095***
	(0.0146)	(0.0144)	(0.0146)	(0.0143)
Recipient donors	0.1036***	0.1167***	0.1047***	0.1172***
	(0.0158)	(0.0150)	(0.0157)	(0.0151)
Log avg. donor capacity	0.0740**	0.0656*	0.0742**	0.0656*
	(0.0266)	(0.0267)	(0.0264)	(0.0265)
Network exposure				
Hub exposure (top 25%)	0.0981***		0.4179**	
	(0.0237)		(0.137)	
Broker exposure (top 25%)		0.0751**		0.4032**
		(0.0234)		(0.154)
Hub × log GDP per capita			−0.0409*	
			(0.0169)	
Broker × log GDP per capita				−0.0420*
				(0.0195)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SEs clustered by country	Yes	Yes	Yes	Yes
Observations	1,321	1,321	1,321	1,321

Notes: Estimates from negative binomial regression models estimated using `fixest`. Hub and broker exposure measure recipients' connections to donors in the top quartile of the donor co-financing network. All models include the full set of controls shown, a Heckman selection correction (IMR), and country and year fixed effects. Standard errors clustered by country are in parentheses. All predictors are lagged by one year. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, $^{\cdot}p < 0.15$.

increase with hub and broker exposure at both low and high levels of income, but the slope of this relationship is substantially steeper when a recipient is at a lower income level (25th percentile of GDP per capita) than when it is at a higher income level (75th percentile), consistent with a negative interaction between network exposure and income.

Substantively, the magnitude of these differences is large. For lower-income recipients at the bottom 25th percentile of GDP per capita, shifting the composition of their donor portfolio from zero to three hub donors is associated with an increase of roughly three additional climate-finance projects, or approximately one additional project per hub donor. Given that the median recipient-year in the sample receives eight projects, this represents a substantial increase relative to what a typical country receives in a year. By contrast, for higher-income recipients at the 75th percentile of GDP per capita, the same compositional shift toward hub donors corresponds to less than half an additional project. A similar pattern holds for exposure to broker donors.



(a) Hub exposure

(b) Broker exposure

Figure 4.1: Predicted project counts by exposure to hubs and brokers for low- and high-income recipients. Predictions are generated from the interaction models and evaluated at the 25th (low) and 75th (high) percentiles of GDP per capita holding covariates constant at their modal values.

We assess whether the results reported above are sensitive to our choice of estimation strategy. Table 4.2 compares the main coefficients from all specifications across negative binomial, Poisson pseudo–maximum likelihood (PPML), and linear fixed-effects regressions. Across all three strategies, the estimated effects of hub and broker exposure are positive and statistically significant in the baseline specifications (columns 1-2). The point estimates are consistent across the count models: in the baseline hub specification, the coefficient is 0.0981 (negative binomial) and 0.0911 (PPML), corresponding to approximately 10.3% and 9.5% increases in expected project counts, respectively. Similarly, for broker exposure, the coefficients are 0.0751 (negative binomial) and 0.0587 (PPML), corresponding to 7.8% and 6.0% increases. The OLS estimates, while on a different scale, also show positive and significant effects.

The interaction specifications (columns 3-4) consistently show that the benefits of network exposure decline as recipient income rises. The negative interaction terms are statistically significant in the negative binomial models (both hub and broker) and OLS models, with the PPML hub interaction also reaching conventional significance. While the PPML broker interaction does not reach conventional significance, the point estimate is negative and of similar magnitude to the negative binomial specification.

Table 4.2: Robustness to Estimation Strategy

	Neg. Binomial				PPML				OLS			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Dependent variable: Annual project count												
Network exposure												
Hub exposure (top 25%)	0.0981***		0.4179**		0.0911***		0.3512*		1.277**		7.601**	
	(0.0237)		(0.137)		(0.0233)		(0.140)		(0.429)		(2.644)	
Broker exposure (top 25%)		0.0751**		0.4032**		0.0587*		0.3232$^{\cdot}$		0.8789$^{\cdot}$		7.733**
		(0.0234)		(0.154)		(0.0234)		(0.167)		(0.478)		(2.680)
Income interaction												
Hub × log GDP per capita			−0.0409*				−0.0333*				−0.8006*	
			(0.0169)				(0.0168)				(0.319)	
Broker × log GDP per capita				−0.0420*				−0.0337				−0.8705**
				(0.0195)				(0.0212)				(0.324)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SEs clustered by country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,321	1,321	1,321	1,321	1,321	1,321	1,321	1,321	1,321	1,321	1,321	1,321

Notes: Table reports key coefficients from the baseline and interaction specifications estimated using different estimation strategy. All models include the full set of controls shown in Table 4.1 and a Heckman selection correction (IMR). Standard errors clustered by country in parentheses. All predictors are lagged by one year. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, $^{\cdot}p < 0.15$.

Regarding our controls, results from the selection equation (Equation 1) are shown in Appendix Table A.5 and are consistent with expectations: countries that are more closely aligned with the United States, more populous, poorer, and more democratic are significantly more likely to receive at least one climate-finance project. The ND-GAIN Country Index, indicating greater climate readiness and lower vulnerability, does not significantly predict entry. This result is not entirely surprising, since the literature examining bilateral flows of climate-related assistance produces mixed results on whether vulnerability significantly correlates with these state-to-state assistance flows (for different findings, see, e.g., Betzold and Weiler (2017); Weiler, Klöck and Dornan (2018); Robinson and Dornan (2016); Stadelmann et al. (2014)).[32]

4.1 Further Robustness Checks

We next examine the robustness of these findings to alternative operationalizations of access to well-connected donors. We re-estimate the main outcome models using alternative measures of donor centrality based on donors' average weighted degree (for hubs) and betweenness centrality (for brokers) in the co-financing network in year $t-1$ (Appendix Table A.6). The positive associations between network exposure and project receipt are substantively unchanged.

As a placebo test, we redefine the key exposure variables as recipients' exposure to *peripheral* donors—those in the bottom 25% of the donor co-financing network—rather than to highly connected hub or broker donors (Appendix Table A.7). Consistent with the proposed informational mechanism, exposure to peripheral donors is negatively associated with project allocations, underscoring that the benefits we identify are specific to connections with well-positioned donors rather than simply reflecting exposure to

[32]In later results, we show that measuring physical vulnerability to climate change with climate-related disasters does not alter this finding.

any set of donors.

We further assess the robustness of the income heterogeneity findings to alternative measures of development. We replace logged GDP per capita with a binary indicator for low-income countries (LIC) using the World Bank's classification scheme (Appendix Table A.8). Consistent with the main results, exposure to hub and broker donors is associated with increased project allocations for low-income recipients. The interaction terms indicate that these network advantages are smaller for non-LIC countries, though the differences are not statistically significant. While this coarser income classification reduces statistical precision, the direction of the effects remains consistent with the main specification.

Both the main effects and the income heterogeneity are robust to alternative operationalizations of key controls. We replace the ND-GAIN index with an annual count of climate-related disasters, capturing acute climate shocks rather than structural vulnerability (Appendix Table A.9); add recipient-level institutional controls, including regulatory quality (Appendix Table A.11), rule of law (Appendix Table A.12), and public sector corruption (Appendix Table A.13), to account for governance characteristics that may affect donor willingness to lend; and substitute our measure of donor capacity with a three-year rolling average of donor climate-finance portfolios, capturing persistent differences in lending capacity rather than short-term fluctuations (Appendix Table A.10). Across all specifications, the network exposure effects remain substantively similar to the main results.

We also assess whether our network exposure measures may be proxying for the regional characteristics of donor IOs rather than the relational advantages arising from their position in the co-financing network. IOs with regional mandates may co-finance more intensively within particular regions, and recipients located in those regions may consequently receive more projects for reasons unrelated to the IOs' position as hubs or brokers in the broader regime complex. To address this possibility, we replace recipient fixed effects with region fixed effects, thereby comparing recipients to other recipients within the same region and year. As shown in Appendix Table A.14, the results are substantively unchanged, indicating that our findings are not driven by regionally concentrated IO activity.

Finally, to ensure our findings are not driven by outlier cases, we re-estimate the main models excluding China and India, the two largest recipients by both population and project counts (Appendix Table A.15). Hub and broker exposure effects remain highly significant with similar magnitudes, demonstrating that the network advantage patterns we identify reflect general dynamics in climate finance allocation rather than being artifacts of the largest recipients.

Taken together, these robustness checks strengthen confidence in our core claim: access to well-positioned donor IOs – to hubs with many partners or to brokers bridging otherwise disconnected groups – generates informational advantages for recipients that translate into greater access to climate-finance projects, and these advantages appear particularly salient for poorer recipients.

4.2 Additional Findings

Recent work by Kaya and Leblebicioğlu (2024) highlights substantial heterogeneity in the climate focus of projects counted as "climate finance." While our main analysis shows that connections to well-positioned IOs increase the receipt of climate finance, these results do not indicate whether exposure to hubs and brokers is disproportionately associated with projects with weaker versus stronger climate focus. To explore this question, we re-estimate our models using a stacked recipient–year–project–type panel.

To do so, we utilize the OECD's marking of the climate component of projects as follows: *principal*, which denotes projects with a fundamental and explicit objective that is central to the project design; *significant*, which includes projects that denote climate change as an important but secondary objective, and *climate components*, i.e., projects where climate considerations play a limited role in project aims. As noted earlier, in our sample, the third category of climate component projects dominate, comprising 64.9% of all climate-marked projects (10,995 of 16,930), while principal and significant projects account for 17.3% (2,924) and 17.8% (3,011), respectively. To differentiate between projects with higher versus lower climate components, we combine principal and significant projects into a single category of *core* projects and contrast these with marginal projects, renaming projects with climate components.

The dependent variable is Y_{itj}, the number of projects of type $j \in \{\text{Core}, \text{Marginal}\}$ received by recipient i in year t. We interact our key network predictors— exposure to hub donors (high degree centrality) and exposure to broker donors (high betweenness centrality)—with an indicator for core projects. Marginal projects serve as the reference category. As a result, the baseline network coefficient captures the association between donor exposure and the number of marginal projects, while the interaction term indicates whether this association differs for core projects. All models use the same selected sample as the main analysis, include the full set of controls, and incorporate year and country fixed effects, with standard errors clustered by recipient.[33]

Table A.16 presents the results. Across both specifications, exposure to well-connected donors is positively associated with the number of marginal climate-marked projects recipients receive. Importantly, we find no evidence that network exposure disproportionately favors marginal projects over substantively meaningful ones. For both hub and broker donor exposure, the interaction terms distinguishing core from marginal projects are small and statistically insignificant, indicating that the association between network exposure and project counts is similar for core and marginal projects.

[33]We estimate the stacked panel using the selected sample from the baseline outcome models and include the IMR estimated from the original first-stage selection equation. We do not re-estimate the selection equation separately for each project type.

Table 4.3: Hub and Broker Effects by Project Climate Focus

	(1) Hub Exposure	(2) Broker Exposure
Dependent variable: Project count by type		
Network exposure (ref.: Marginal projects)		
Hub exposure (top 25%)	0.0898***	
	(0.0258)	
Broker exposure (top 25%)		0.0494*
		(0.0302)
Exposure × Core (Principal & Significant)	0.0020	0.0343
	(0.0458)	(0.0470)
Controls	Yes	Yes
Country FE	Yes	Yes
Year FE	Yes	Yes
SEs clustered by country	Yes	Yes
Observations	3,972	3,972

Notes: Estimates from Poisson pseudo–maximum likelihood (PPML). Both models include the full set of controls shown in Table 4.1, country and year fixed effects, and an inverse Mills ratio (IMR) derived from the baseline first-stage probit selection equation. The dependent variable distinguishes between marginal projects (reference category) and core projects (principal and significant). The interaction term captures whether exposure to hub or broker donors differentially affects the allocation of core projects relative to marginal ones. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

5 Conclusion

Global governance has become increasingly complex, marked by overlapping international organizations operating within the same issue areas and interacting in evolving ways. While existing scholarship has shown that such complexity shapes cooperation and outcomes, less is known about how the structure of these interactions affects the distribution of the goods that regimes provide. This article addresses this crucial question by examining how relational structures within complex regimes condition access to multilateral climate finance.

Focusing on multilateral climate finance—a domain in which distributional conflict between richer and developing countries is particularly salient—we integrate insights from regime complexity and network analysis, two literatures that share a concern with relational dynamics but have rarely been applied together systematically. We argue and show that access to climate finance depends not only on donor or recipient state characteristics but also on patterns of cooperation among international organizations through which financing is delivered.

Our theory suggests that inter-organizational cooperation facilitates informational flows among IOs with significant downstream consequences for recipient states. International organizations that collaborate widely with their peers are better informed about the standards, procedures, and priorities that govern competitive project priorities and preferences across the regime. By the same token, recipients that are connected to these well-positioned IOs receive more goods; through their network positions, well-positioned IOs can transmit valuable information that increases the capacity of recipient states by lowering informational asymmetries. States that are connected to well-positioned actors can also better signal their credibility as recipients to the rest of the network. These informational flows are particularly important in high complexity environments.

Empirically, we operationalize inter-organizational cooperation using project-level co-financing relationships, which capture the formal pooling of financial and technical resources in pursuit of shared interventions. This measure aligns closely with our theoretical framework, as co-financing is a plausible setting for learning about other organizations' practices and expectations. Mapping these relationships reveals substantial variation in the network positions of IOs, including the presence of hubs and brokers that connect different parts of the regime complex.

We show that recipient states connected to hub and broker IOs receive more climate finance projects, with particularly strong effects for lower-income developing countries. These countries benefit disproportionately from access to well-positioned organizations because the informational advantages conveyed through these ties substitute for limited domestic capacity to navigate institutional complexity independently. In this way, regime complexity shapes distribution not merely through the proliferation of institutions but also through the relational pathways linking recipients to key organizational actors. More broadly, these findings suggest that important IOs are not just those that are large and well-resourced, but also those that are well-positioned (relative to their peers) within regime complexes.

The implications of these findings extend beyond climate finance to other areas of development and military assistance characterized by complex regimes. Future research could investigate how the shifting positions of IOs and states within inter-organizational cooperation networks shape access to regime-provided goods across issue areas. Future work could also explore how macro-level features of regime complexes condition the value of different network positions. Greater centralization may amplify the importance of hub organizations as focal points of information and gate-keeping, while lower density may increase the relevance of brokers that bridge otherwise weakly connected clusters.

By more systematically integrating network analysis into the study of regime complexity, scholars can better understand how evolving institutional structures (re)distribute informational advantages—and, ultimately, material benefits—across recipients in global governance. In the case of this study, we show that the relations among IOs providing multilateral climate finance – which is critical to achieving the global public good of climate stability—have a bearing on the distribution of climate finance. Efforts to strengthen the impact of climate finance and other dimensions of multilateral assistance would thus benefit from a closer consideration of the evolving network of relationships through which they operate.

A Appendix

A.1 Descriptive Information

Table A.1: Illustrative Sample of Climate Finance Projects

Country	Implementing IO	Year	Project title	Climate value
China	Asian Development Bank	2020	Anhui Huangshan Xin'an River Ecological Protection and Green Development Project	Components
Djibouti	World Bank	2016	Rural Community Development and Water Mobilization Project	Components
Egypt	Global Environment Facility	2013	Promoting Low-Carbon Technologies for Cooling and Heating in Industrial Applications	Principal
India	Global Environment Facility	2019	Sustainable Cities Impact Program	Principal
Madagascar	Green Climate Fund	2016	Sustainable Landscapes in Eastern Madagascar	Significant
Mexico	World Bank	2020	Solar Energy for Centralized Grids	Principal
Togo	Adaptation Fund	2021	Scaling Up Climate-Resilient Rice Production	Principal

Note: Randomly selected projects shown for illustrative purposes. "Principal" and "Significant" indicate projects with a greater focus on climate change, whereas "Components" refers to projects that include climate-related components but are not primarily climate-focused.

Table A.2: International Organizations in the Dataset

IO	Full Name
AF	Adaptation Fund
AIIB	Asian Infrastructure Investment Bank
AfDB	African Development Bank
AsDB	Asian Development Bank
BSTDB	Black Sea Trade and Development Bank
CABEI	Central American Bank for Economic Integration
CAF	Development Bank of Latin America
CarDB	Caribbean Development Bank
CEB	Council of Europe Development Bank
CIF	Climate Investment Funds
EBRD	European Bank for Reconstruction and Development
EIB	European Investment Bank
FAO	Food and Agriculture Organization of the United Nations
GCF	Green Climate Fund
GEF	Global Environment Facility
GGGI	Global Green Growth Institute
IDB	Inter-American Development Bank
IFAD	International Fund for Agricultural Development
IMF-RST	IMF Resilience and Sustainability Trust
IsDB	Islamic Development Bank
NDF	Nordic Development Fund
WBG	World Bank Group

Table A.3: Codebook

Variable	Description
Project Count	Number of distinct multilateral climate-finance projects received by recipient r in year t.
Recipient Donors	Number of distinct donor organizations financing recipient r in year $t-1$.
Commitment Amount	Total amount of climate-related finance committed to recipient r in constant USD in year $t-1$. Logged in regression models.

Continued on next page

Table A.3 – continued from previous page

Variable	Description
Hub Donors (Top Quartile)	Number of donors financing recipient r whose weighted degree centrality lies above the 75th percentile of the donor co-financing network in year $t-1$.
Hub Donors (Bottom Quartile)	Number of donors financing recipient r whose weighted degree centrality lies at or below the 25th percentile of the donor co-financing network in year $t-1$.
Bridge Donors (Top Quartile)	Number of donors financing recipient r whose weighted betweenness centrality lies above the 75th percentile of the donor co-financing network in year $t-1$.
Bridge Donors (Bottom Quartile)	Number of donors financing recipient r whose weighted betweenness centrality lies at or below the 25th percentile of the donor co-financing network in year $t-1$.
Average Donor Degree	Average weighted degree of donors financing recipient r in year $t-1$, where weights reflect the number of shared projects donors have with other donors in the global co-financing network.
Average Donor Betweenness	Average weighted betweenness centrality of donors financing recipient r in year $t-1$. Betweenness is computed using inverse edge weights so that stronger co-financing ties correspond to shorter network distances.
Active Donors	Total number of donor organizations with any multilateral climate-finance activity in the OECD CRS in year $t-1$.
Average Donor Capacity	Average size of the climate-finance portfolios of the donor organizations financing recipient r in year $t-1$. Donor capacity is measured as each donor's total climate-finance commitments across all recipients in a given year, and the recipient-level measure is constructed as the mean of these donor-level totals.
Average Donor Capacity (3-year smoothed)	Average size of the climate-finance portfolios of the donor organizations financing recipient r in year $t-1$, where donor capacity is first smoothed using a three-year rolling mean.

Continued on next page

Table A.3 – continued from previous page

Variable	Description
Network Density	Density of the global donor co-financing network in year $t-1$, measured as the ratio of realized donor–donor ties to all possible ties among active revealed donors.
Network Centralization	Freeman degree centralization of the global donor co-financing network in year $t-1$, capturing the extent to which co-financing activity is concentrated around a small number of dominant donors.
nonLIC	Indicator equal to 0 if the recipient is classified by the World Bank as a Low Income Country, and 1 otherwise.
GDP per Capita	Gross domestic product per capita in constant USD in year $t-1$ (World Bank). Logged in regression models.
Population	Total population of the recipient country in year $t-1$ (World Bank). Logged in regression models.
ND-GAIN Index	Notre Dame Global Adaptation Initiative (ND-GAIN) Country Index of recipient in year $t-1$ measuring vulnerability and readiness across six sectors: food, water, health, ecosystem services, human habitat, and infrastructure.
CO_2 Emissions	Annual carbon dioxide emissions in kilotons of recipient in year $t-1$.
Disasters	Number of climate-related natural disasters experienced by the recipient in year $t-1$, including droughts, floods, wildfires, and extreme temperature events.
Rule of Law	Index measuring the extent to which laws are publicly known, enforced, and applied equally, capturing the predictability and credibility of legal institutions (V-Dem: *v2x_rule*). Ranges 0 to 1. Lagged by one year.
Public Sector Corruption	Index capturing the extent to which public sector employees grant favors in exchange for bribes, kickbacks, or other material inducement (V-Dem: *v2x_pubcorr*). Ranges from 0 to 1. Higher values indicate greater corruption. Lagged by one year.

Continued on next page

Table A.3 – continued from previous page

Variable	Description
Electoral Democracy	Index measuring the extent to which the ideal of electoral democracy is achieved (V-Dem: *v2x_polyarchy*). Ranges 0 to 1. Higher values indicate more democratic political institutions. Lagged by one year.
UNSC Membership	Indicator equal to 1 if the recipient held a non-permanent seat on the United Nations Security Council in year $t-1$, and 0 otherwise.
UNGA Ideal Point Difference	Absolute difference between the recipient's and the United States' ideal points in the UN General Assembly in year $t-1$, based on voting similarity scores. Higher values indicate greater policy divergence from the United States.

Table A.4: Summary Statistics

Panel A. Outcome Sample (Eligible, Conditional on Project Receipt)

Variable	Min	25th pctl	Median	Mean	75th pctl	Max
Recipient donors (lag)	0	1	2	2.62	4	10
Hub exposure (top 25%, lag)	0	0	1	0.89	1	4
Broker exposure (top 25%, lag)	0	0	1	0.80	1	4
Log donor capacity (lag)	0.00	14.02	14.85	14.55	15.36	16.53
Net density (lag)	0.00	0.26	0.33	0.34	0.44	0.61
Net centralization (lag)	0.00	0.25	0.29	0.27	0.33	0.43
ND-GAIN index (lag)	25.84	38.66	43.99	44.00	48.69	61.96
CO_2 emissions (lag)	-81.75	34.18	148.42	543.03	280.84	44,517.65
Disasters (lag)	0	0	1	1.84	2	34
Log population (lag)	9.23	14.79	16.11	15.80	17.22	21.07
Log GDP per capita (lag)	5.35	7.22	8.16	7.99	8.74	9.86
UNSC member (lag)	0	0	0	0.056	0	1
UNGA ideal-point distance to U.S. (lag)	0.538	2.781	3.112	3.020	3.339	4.754
Democracy (V-Dem Polyarchy, lag)	0.068	0.297	0.498	0.467	0.606	0.912
Log commitments (lag)	1.063	9.499	10.964	10.751	12.247	15.336
Project count (DV)	1	3	8	13.07	18	115

Panel B. Selection Sample (All Eligible Recipient–Years)

Variable	Min	25th pctl	Median	Mean	75th pctl	Max
ND-GAIN index (lag)	25.41	38.70	44.79	44.28	48.85	63.25
CO_2 emissions (lag)	-81.75	0.00	129.41	508.21	252.98	44,517.65
Disasters (lag)	0	0	1	1.63	2	34
Log population (lag)	9.212	14.120	15.833	15.451	17.105	21.070
Log GDP per capita (lag)	5.294	7.228	8.230	8.096	8.903	10.541
UNSC member (lag)	0	0	0	0.046	0	1
UNGA ideal-point distance to U.S. (lag)	0.044	2.790	3.076	2.999	3.317	4.800
Democracy (V-Dem Polyarchy, lag)	0.068	0.294	0.514	0.468	0.606	0.912

Note: Panel A reports statistics for the outcome-model sample (1,324 recipient–years, conditional on project receipt). Panel B reports statistics for the broader selection sample (1,988 eligible recipient–years). Variables are lagged or logged where indicated, consistent with the main specifications. Missing macroeconomic covariates are imputed using with standard methods for panel data (Within-country linear interpolation followed by forward- and backward-filling, with median imputation for remaining missing values.).

A.2 Selection Stage Results and Instrument Diagnostics

Table A.5 reports the first-stage probit model estimating selection into multilateral climate finance. The model includes year fixed effects and a range of lagged political, economic, and environmental controls. Country fixed effects are excluded from the selection equation because they would absorb most cross-national variation in political alignment and induce separation in the nonlinear probit model. Variables capturing prior donor relationships and funding intensity (e.g., prior commitments, number of donors, and donor capacity) are also excluded from the selection equation because they are related to prior project receipt and induce separation in the nonlinear probit model. These factors are instead modeled in the outcome equation, where they capture path dependence conditional on entry.

The results show that UNGA ideal-point distance from the United States is a strong predictor of entry into climate finance. A one-unit increase in idealpointdiff reduces the probability of selection by 3.53 percentage points, on average (AME = 0.035, $p < 0.05$). To assess the plausibility of the exclusion restriction, we re-estimate the outcome equation on the selected sample, including UNGA ideal-point distance as a regressor alongside country and year fixed effects, with standard errors clustered by country. Political alignment does not significantly predict the number of climate-finance projects a country receives once it has entered the system ($\beta = -2.0$, SE = 2.0, $p > 0.10$), consistent with the exclusion assumption (here, that diplomatic alignment affects entry into climate finance but not project allocations conditional on selection).

Table A.5: First Stage: Probit Model of Selection into Climate Finance

	Selected (1 = Received $\geq$ 1 Project in year t)
UNGA ideal-point distance to U.S. (lag)	-0.153^{*} (0.071)
ND_GAIN index (lag)	$0.015^{\dagger}$ (0.008)
CO_2 emissions (lag)	0.012 (0.012)
Log population	0.123^{***} (0.016)
Log GDP per capita	-0.380^{***} (0.054)
UNSC member (lag)	0.626^{**} (0.193)
Democracy (V-Dem Polyarchy)	0.626^{**} (0.211)
Year fixed effects	Yes
Observations	1,952

Note: Probit estimates. Standard errors clustered by country in parentheses. All covariates are lagged by one year. Country fixed effects are excluded because entry into climate finance is largely a one-time decision with limited within-country variation, which would absorb nearly all identifying variation and induce separation in the probit model. Countries that are more diplomatically distant from the United States (higher UNGA ideal-point distance values) are significantly less likely to receive any climate-finance project. More populous, poorer, and democratic countries are significantly more likely to receive at least one climate-finance project, as are temporary UNSC members. $^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

A.3 Robustness Tests

Table A.6: Alternative Operationalization of Exposure to Hubs and Brokers

	(1)	(2)	(3)	(4)
Dependent variable: Annual project count				
ND-GAIN index	−0.0071	−0.0071	−0.0073	−0.0070
	(0.0148)	(0.0151)	(0.0149)	(0.0153)
CO_2 emissions (log)	−0.0179	−0.0189	−0.0179	−0.0187
	(0.0225)	(0.0222)	(0.0226)	(0.0221)
Log population	1.592***	1.733***	1.581***	1.743***
	(0.370)	(0.373)	(0.374)	(0.381)
Log GDP per capita	0.2227·	0.2300·	0.2273·	0.2279·
	(0.129)	(0.127)	(0.132)	(0.126)
UNSC member	0.0131	0.0098	0.0110	0.0111
	(0.0726)	(0.0711)	(0.0731)	(0.0714)
V-Dem Polyarchy	−0.1149	−0.0526	−0.1192	−0.0509
	(0.246)	(0.250)	(0.246)	(0.249)
Log commitment amount	0.2159***	0.2116***	0.2157***	0.2116***
	(0.0147)	(0.0145)	(0.0147)	(0.0145)
Recipient donors	0.1365***	0.1399***	0.1368***	0.1398***
	(0.0139)	(0.0142)	(0.0139)	(0.0142)
Log avg. donor capacity	0.0921**	0.0675*	0.0920**	0.0676*
	(0.0282)	(0.0276)	(0.0282)	(0.0276)
Network exposure				
Avg. donor degree	0.0017***		0.0021·	
	(0.0003)		(0.0012)	
Avg. donor betweenness		0.0066**		0.0049
		(0.0020)		(0.0112)
Avg. donor degree × log GDP/cap			-4.09×10^{-5}	
			(0.0002)	
Avg. donor betweenness × log GDP/cap				0.0002
				(0.0014)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SEs clustered by country	Yes	Yes	Yes	Yes
Observations	1,321	1,321	1,321	1,321

Notes: Negative binomial regression models estimated using `fixest`. Network exposure is alternatively operationalized using the average donor degree centrality of donors funding a recipient at $t-1$ (Columns 1 and 3) and the average donor betweenness centrality of donors funding a recipient at $t-1$ (Columns 2 and 4). All models include a Heckman selection correction (IMR). Standard errors clustered by country in parentheses. All predictors are lagged by one year. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, $^{\cdot}p < 0.15$.

Table A.7: Placebo: Exposure to Peripheral Donors (Bottom 25%)

	(1)	(2)
Dependent variable: Annual project count		
ND-GAIN index	−0.0068	−0.0078
	(0.0148)	(0.0154)
CO_2 emissions (log)	−0.0197	−0.0194
	(0.0220)	(0.0219)
Log population	1.791***	1.804***
	(0.376)	(0.376)
Log GDP per capita	0.2227·	0.2322·
	(0.127)	(0.127)
UNSC member	0.0044	0.0056
	(0.0700)	(0.0697)
V-Dem Polyarchy	−0.0662	−0.0307
	(0.253)	(0.253)
Log commitment amount	0.2091***	0.2101***
	(0.0144)	(0.0143)
Recipient donors	0.1500***	0.1707***
	(0.0149)	(0.0194)
Log avg. donor capacity	0.0718*	0.0636*
	(0.0287)	(0.0271)
Network exposure (placebo)		
Peripheral hub exposure (bottom 25%)	−0.0464*	
	(0.0228)	
Peripheral broker exposure (bottom 25%)		−0.0497*
		(0.0206)
Country FE	Yes	Yes
Year FE	Yes	Yes
SEs clustered by country	Yes	Yes
Observations	1,321	1,321

Notes: Negative binomial regression models estimated using `fixest`. As a placebo test, the key exposure variables are redefined as recipients' exposure to *peripheral* donors (those in the bottom 25% of the donor co-financing network), rather than to highly connected hub or broker donors. Consistent with the proposed informational mechanism, exposure to peripheral donors is negatively associated with projects received, suggesting that well-connected donors provide unique advantages. All models include a Heckman selection correction (IMR). Standard errors clustered by country in parentheses. All predictors are lagged by one year. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, $^{\cdot}p < 0.15$.

Table A.8: World Bank Low-Income Classification (LIC vs. Non-LIC)

	(1)	(2)
Dependent variable: Annual project count		
ND-GAIN index	−0.0059	−0.0068
	(0.0163)	(0.0166)
CO_2 emissions (log)	−0.0116	−0.0133
	(0.0216)	(0.0227)
Log population	1.381***	1.530***
	(0.385)	(0.389)
UNSC member	0.0280	0.0380
	(0.0722)	(0.0684)
V-Dem Polyarchy	−0.0185	0.0698
	(0.243)	(0.244)
Log commitment amount	0.2126***	0.2101***
	(0.0146)	(0.0144)
Recipient donors	0.1042***	0.1171***
	(0.0160)	(0.0152)
Log avg. donor capacity	0.0756**	0.0669*
	(0.0266)	(0.0267)
Network exposure		
Hub exposure (top 25%)	0.1231**	
	(0.0401)	
Broker exposure (top 25%)		0.0930*
		(0.0364)
LIC interactions		
Non-LIC	−0.0146	−0.0324
	(0.0893)	(0.0940)
Hub × Non-LIC	−0.0334	
	(0.0387)	
Broker × Non-LIC		−0.0232
		(0.0387)
Country FE	Yes	Yes
Year FE	Yes	Yes
SEs clustered by country	Yes	Yes
Observations	1,319	1,319

Notes: Negative binomial regression models estimated using `fixest`. Logged GDP per capita is replaced with a binary indicator for World Bank low-income countries (LIC), with LICs as the reference category. Consistent with the baseline results, exposure to hub and broker donors is associated with increased project allocations for low-income recipients. Interaction terms indicate smaller effects for non-LIC countries, though differences are not statistically significant. All models include a Heckman selection correction (IMR). Standard errors clustered by country in parentheses. All predictors are lagged by one year. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.9: Alternative Measure of Climate Need: Disasters

	(1)	(2)	(3)	(4)
Dependent variable: Annual project count				
Climate-related disasters	0.0095	0.0109	0.0096	0.0103
	(0.0082)	(0.0089)	(0.0079)	(0.0081)
CO_2 emissions (log)	−0.0203	−0.0216	−0.0229	−0.0248
	(0.0216)	(0.0224)	(0.0217)	(0.0219)
Log population	1.622***	1.730***	1.442***	1.582***
	(0.373)	(0.377)	(0.374)	(0.382)
Log GDP per capita	0.2414·	0.2413·	0.2750*	0.2713*
	(0.127)	(0.127)	(0.127)	(0.128)
UNSC member	−0.0052	0.0020	−0.0227	−0.0132
	(0.0729)	(0.0696)	(0.0746)	(0.0704)
V-Dem Polyarchy	−0.1069	−0.0366	−0.1688	−0.0722
	(0.249)	(0.248)	(0.247)	(0.247)
Log commitment amount	0.2127***	0.2106***	0.2132***	0.2100***
	(0.0147)	(0.0145)	(0.0147)	(0.0145)
Recipient donors	0.1032***	0.1160***	0.1042***	0.1165***
	(0.0158)	(0.0150)	(0.0157)	(0.0151)
Log avg. donor capacity	0.0744**	0.0662*	0.0748**	0.0664*
	(0.0267)	(0.0268)	(0.0265)	(0.0266)
Network exposure				
Hub exposure (top 25%)	0.0972***		0.4076**	
	(0.0237)		(0.134)	
Broker exposure (top 25%)		0.0747**		0.3878**
		(0.0233)		(0.146)
Hub × log GDP per capita			−0.0397*	
			(0.0166)	
Broker × log GDP per capita				−0.0401*
				(0.0184)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SEs clustered by country	Yes	Yes	Yes	Yes
Observations	1,321	1,321	1,321	1,321

Notes: Negative binomial regression models estimated using `fixest`. ND-GAIN is replaced with an annual count of climate-related disasters to proxy climate need. Results for hub and broker exposure remain substantively unchanged. All models include a Heckman selection correction (IMR). All predictors are lagged by one year. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, $^{\cdot}p < 0.15$.

Table A.10: Alternative Measure of Donor Capacity: Three-Year Rolling Average

	(1)	(2)	(3)	(4)
Dependent variable: Annual project count				
ND-GAIN index	−0.0072	−0.0082	−0.0103	−0.0102
	(0.0156)	(0.0158)	(0.0152)	(0.0154)
CO_2 emissions (log)	−0.0182	−0.0199	−0.0206	−0.0232
	(0.0207)	(0.0215)	(0.0207)	(0.0209)
Log population	1.650***	1.738***	1.474***	1.582***
	(0.375)	(0.381)	(0.376)	(0.384)
Log GDP per capita	0.2439*	0.2418*	0.2797*	0.2753*
	(0.123)	(0.123)	(0.123)	(0.123)
UNSC member	−0.0003	0.0054	−0.0183	−0.0110
	(0.0726)	(0.0695)	(0.0743)	(0.0705)
V-Dem Polyarchy	−0.0646	−0.0022	−0.1192	−0.0350
	(0.250)	(0.249)	(0.246)	(0.246)
Log commitment amount	0.2232***	0.2196***	0.2238***	0.2190***
	(0.0144)	(0.0141)	(0.0143)	(0.0139)
Recipient donors	0.1012***	0.1129***	0.1023***	0.1134***
	(0.0157)	(0.0148)	(0.0156)	(0.0149)
Log avg. donor capacity (3yr rolling)	0.0104·	0.0106·	0.0103·	0.0107·
	(0.0054)	(0.0055)	(0.0054)	(0.0055)
Network exposure				
Hub exposure (top 25%)	0.0890***		0.4057**	
	(0.0236)		(0.137)	
Broker exposure (top 25%)		0.0705**		0.4004**
		(0.0235)		(0.153)
Hub × log GDP per capita			−0.0405*	
			(0.0168)	
Broker × log GDP per capita				−0.0422*
				(0.0193)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SEs clustered by country	Yes	Yes	Yes	Yes
Observations	1,321	1,321	1,321	1,321

Notes: Negative binomial regression models estimated using `fixest`. Average donor capacity is replaced with a three-year rolling mean of donor organizations' total climate-finance commitments, lagged one year, to capture persistent differences in donor lending capacity rather than short-term fluctuations. Results for hub and broker exposure remain substantively unchanged. All models include a Heckman selection correction (IMR). All predictors are lagged by one year. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, $^{\cdot}p < 0.15$.

Table A.11: Alternative Recipient Governance Control: Regulatory Quality

	(1)	(2)	(3)	(4)
Dependent variable: Annual project count				
ND-GAIN index	−0.0132	−0.0133	−0.0168	−0.0157
	(0.0142)	(0.0145)	(0.0139)	(0.0143)
CO_2 emissions (log)	−0.0238	−0.0242	−0.0267	−0.0278
	(0.0219)	(0.0229)	(0.0222)	(0.0225)
Log population	1.771***	1.872***	1.600***	1.722***
	(0.396)	(0.400)	(0.395)	(0.399)
Log GDP per capita	0.2030	0.2099$^{\cdot}$	0.2345$^{\cdot}$	0.2406$^{\cdot}$
	(0.126)	(0.126)	(0.126)	(0.127)
UNSC member	0.0045	0.0077	−0.0105	−0.0067
	(0.0693)	(0.0660)	(0.0710)	(0.0672)
Regulatory quality	0.1523	0.1315	0.1547	0.1342
	(0.115)	(0.118)	(0.115)	(0.118)
Log commitment amount	0.2115***	0.2094***	0.2119***	0.2088***
	(0.0147)	(0.0145)	(0.0147)	(0.0144)
Recipient donors	0.1020***	0.1155***	0.1031***	0.1159***
	(0.0159)	(0.0150)	(0.0158)	(0.0151)
Log avg. donor capacity	0.0730**	0.0649*	0.0729**	0.0648*
	(0.0265)	(0.0265)	(0.0263)	(0.0263)
Network exposure				
Hub exposure (top 25%)	0.0997***		0.4152**	
	(0.0236)		(0.138)	
Broker exposure (top 25%)		0.0760**		0.4045**
		(0.0232)		(0.153)
Hub × log GDP per capita			−0.0404*	
			(0.0169)	
Broker × log GDP per capita				−0.0420*
				(0.0194)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SEs clustered by country	Yes	Yes	Yes	Yes
Observations	1,321	1,321	1,321	1,321

Notes: Negative binomial regression models estimated using `fixest`. These models replace the baseline democracy control (V-Dem Polyarchy) with the World Bank Worldwide Governance Indicator for regulatory quality. Results for hub and broker exposure are substantively unchanged. All models include the full set of controls shown and a Heckman selection correction (IMR). All predictors are lagged by one year. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, $^{\cdot}p < 0.15$.

Table A.12: Alternative Recipient Governance Control: Rule of Law

	(1)	(2)	(3)	(4)
Dependent variable: Annual project count				
ND-GAIN index	−0.0092	−0.0101	−0.0123	−0.0120
	(0.0152)	(0.0154)	(0.0149)	(0.0151)
CO_2 emissions (log)	−0.0209	−0.0219	−0.0235	−0.0251
	(0.0213)	(0.0222)	(0.0215)	(0.0217)
Log population	1.650***	1.761***	1.486***	1.620***
	(0.379)	(0.384)	(0.379)	(0.384)
Log GDP per capita	0.2079	0.2114	0.2411·	0.2438·
	(0.129)	(0.129)	(0.129)	(0.130)
UNSC member	0.0133	0.0173	−0.0030	0.0015
	(0.0703)	(0.0671)	(0.0721)	(0.0683)
Rule of law	0.2830	0.2915	0.2423	0.2469
	(0.237)	(0.238)	(0.240)	(0.243)
Log commitment amount	0.2115***	0.2094***	0.2120***	0.2089***
	(0.0146)	(0.0143)	(0.0146)	(0.0143)
Recipient donors	0.1036***	0.1164***	0.1047***	0.1169***
	(0.0157)	(0.0149)	(0.0156)	(0.0150)
Log avg. donor capacity	0.0728**	0.0649*	0.0727**	0.0648*
	(0.0268)	(0.0268)	(0.0266)	(0.0267)
Network exposure				
Hub exposure (top 25%)	0.0982***		0.4023**	
	(0.0239)		(0.138)	
Broker exposure (top 25%)		0.0760**		0.3900*
		(0.0233)		(0.154)
Hub × log GDP per capita			−0.0390*	
			(0.0170)	
Broker × log GDP per capita				−0.0402*
				(0.0196)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SEs clustered by country	Yes	Yes	Yes	Yes
Observations	1,321	1,321	1,321	1,321

Notes: Negative binomial regression models estimated using `fixest`. These models replace the baseline democracy control (V-Dem Polyarchy) with a measure of recipient rule of law. Results for hub and broker exposure remain substantively unchanged. All models include a Heckman selection correction (IMR). All predictors are lagged by one year. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, $^{\cdot}p < 0.15$.

Table A.13: Alternative Governance Control: Public Sector Corruption

	(1)	(2)	(3)	(4)
Dependent variable: Annual project count				
ND-GAIN index	−0.0074	−0.0083	−0.0107	−0.0103
	(0.0152)	(0.0154)	(0.0149)	(0.0151)
CO_2 emissions (log)	−0.0206	−0.0215	−0.0235	−0.0251
	(0.0215)	(0.0224)	(0.0216)	(0.0218)
Log population	1.678***	1.790***	1.505***	1.639***
	(0.369)	(0.373)	(0.368)	(0.371)
Log GDP per capita	0.2260·	0.2298·	0.2590*	0.2620*
	(0.122)	(0.122)	(0.122)	(0.123)
UNSC member	−0.0008	0.0028	−0.0170	−0.0127
	(0.0698)	(0.0664)	(0.0716)	(0.0677)
Public sector corruption	0.0659	0.0627	0.1083	0.1036
	(0.239)	(0.240)	(0.239)	(0.241)
Log commitment amount	0.2122***	0.2101***	0.2127***	0.2096***
	(0.0147)	(0.0145)	(0.0147)	(0.0144)
Recipient donors	0.1038***	0.1167***	0.1049***	0.1172***
	(0.0158)	(0.0150)	(0.0158)	(0.0151)
Log avg. donor capacity	0.0736**	0.0656*	0.0735**	0.0655*
	(0.0265)	(0.0266)	(0.0263)	(0.0264)
Network exposure				
Hub exposure (top 25%)	0.0980***		0.4166**	
	(0.0238)		(0.138)	
Broker exposure (top 25%)		0.0753**		0.4071**
		(0.0234)		(0.155)
Hub × log GDP per capita			−0.0408*	
			(0.0170)	
Broker × log GDP per capita				−0.0425*
				(0.0196)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SEs clustered by country	Yes	Yes	Yes	Yes
Observations	1,321	1,321	1,321	1,321

Notes: Negative binomial regression models estimated using `fixest`. These models replace the baseline democracy control (V-Dem Polyarchy) with a measure of recipient public sector corruption. Results for hub and broker exposure remain substantively unchanged. All models include the full set of controls shown and a Heckman selection correction (IMR). All predictors are lagged by one year. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, $^{\cdot}p < 0.15$.

Table A.14: Region Fixed Effects

	(1)	(2)	(3)	(4)
Dependent variable: Annual project count				
ND-GAIN index	0.0055	0.0062	0.0045	0.0054
	(0.0058)	(0.0056)	(0.0057)	(0.0056)
CO_2 emissions (log)	0.0017	0.0019	0.0003	0.0006
	(0.0075)	(0.0073)	(0.0075)	(0.0073)
Log population	0.0111	0.0130	0.0053	0.0071
	(0.0183)	(0.0181)	(0.0179)	(0.0176)
Log GDP per capita	-0.1622^{**}	-0.1636^{**}	-0.0700	-0.0732
	(0.0562)	(0.0552)	(0.0660)	(0.0651)
UNSC member	0.0169	0.0271	-0.0167	-0.0082
	(0.0768)	(0.0755)	(0.0772)	(0.0745)
V-Dem Polyarchy	-0.0767	-0.0689	-0.1172	-0.1106
	(0.166)	(0.163)	(0.166)	(0.163)
Log commitment amount	0.2313^{***}	0.2302^{***}	0.2312^{***}	0.2294^{***}
	(0.0140)	(0.0138)	(0.0138)	(0.0137)
Recipient donors	0.1296^{***}	0.1366^{***}	0.1315^{***}	0.1380^{***}
	(0.0184)	(0.0165)	(0.0184)	(0.0165)
Log avg. donor capacity	0.0979^{***}	0.0939^{***}	0.0973^{***}	0.0924^{***}
	(0.0257)	(0.0255)	(0.0253)	(0.0253)
Network exposure				
Hub exposure (top 25%)	0.0887^{***}		0.5174^{***}	
	(0.0233)		(0.141)	
Broker exposure (top 25%)		0.0859^{***}		0.5643^{***}
		(0.0239)		(0.149)
Hub × log GDP per capita			-0.0551^{**}	
			(0.0179)	
Broker × log GDP per capita				-0.0614^{**}
				(0.0190)
Region FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SEs clustered by country	Yes	Yes	Yes	Yes
Observations	1,324	1,324	1,324	1,324

Notes: Estimates from negative binomial regression models estimated using `fixest`. Models replace country fixed effects with region fixed effects, comparing recipient countries to other recipients within the same region. All models include the full set of controls shown and a Heckman selection correction (IMR). Standard errors clustered by country in parentheses. All predictors are lagged by one year. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.15: Excluding China and India

	(1)	(2)	(3)	(4)
Dependent variable: Annual project count				
ND-GAIN index	-0.0011	-0.0017	-0.0048	-0.0040
	(0.0172)	(0.0172)	(0.0169)	(0.0171)
CO_2 emissions (log)	-0.0207	-0.0223	-0.0230	-0.0247
	(0.0214)	(0.0223)	(0.0215)	(0.0218)
Log population	1.632^{***}	1.730^{***}	1.475^{***}	1.625^{***}
	(0.371)	(0.373)	(0.372)	(0.378)
Log GDP per capita	$0.2340^{\cdot}$	$0.2362^{\cdot}$	0.2671^{*}	0.2604^{*}
	(0.128)	(0.128)	(0.129)	(0.129)
UNSC member	-0.0122	-0.0103	-0.0297	-0.0228
	(0.0761)	(0.0720)	(0.0777)	(0.0731)
V-Dem Polyarchy	-0.0692	-0.0050	-0.1161	-0.0267
	(0.258)	(0.259)	(0.255)	(0.257)
Log commitment amount	0.2110^{***}	0.2089^{***}	0.2113^{***}	0.2085^{***}
	(0.0148)	(0.0146)	(0.0148)	(0.0145)
Recipient donors	0.1076^{***}	0.1182^{***}	0.1088^{***}	0.1188^{***}
	(0.0159)	(0.0153)	(0.0159)	(0.0154)
Log avg. donor capacity	0.0733^{**}	0.0663^{*}	0.0734^{**}	0.0661^{*}
	(0.0265)	(0.0266)	(0.0264)	(0.0265)
IMR	-0.0765	-0.0736	-0.1887	-0.1532
	(0.295)	(0.292)	(0.301)	(0.298)
Network exposure				
Hub exposure (top 25%)	0.0937^{***}		0.3847^{**}	
	(0.0243)		(0.136)	
Broker exposure (top 25%)		0.0783^{***}		0.3218^{*}
		(0.0234)		(0.143)
Hub × log GDP per capita			-0.0373^{*}	
			(0.0168)	
Broker × log GDP per capita				$-0.0313^{\cdot}$
				(0.0179)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SEs clustered by country	Yes	Yes	Yes	Yes
Observations	1,303	1,303	1,303	1,303
Pseudo R^2	0.245	0.244	0.246	0.245

Notes: Negative binomial regression models estimated using `fixest`, excluding China and India. These two countries are the largest recipients by both population and total project volume. Results for hub and broker exposure remain substantively unchanged, demonstrating that the findings are not driven by these outlier cases. All models include a Heckman selection correction (IMR). Standard errors clustered by country in parentheses. All predictors are lagged by one year. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, $^{\cdot}p < 0.15$.

Table A.16: Results by Project Climate Focus

	(1) Hub Exposure	(2) Broker Exposure
Dependent variable: Project count by type		
ND-GAIN index	-0.0125^{*}	-0.0120^{*}
	(0.0055)	(0.0052)
CO_2 emissions (log)	-0.0060	-0.0063
	(0.0102)	(0.0099)
Log population	0.0223	0.0225
	(0.0173)	(0.0167)
UNSC member	0.0096	0.0184
	(0.0670)	(0.0659)
V-Dem Polyarchy	-0.1419	-0.1337
	(0.1391)	(0.1345)
Log commitment amount	0.2297^{***}	0.2289^{***}
	(0.0165)	(0.0163)
Recipient donors	0.1269^{***}	0.1318^{***}
	(0.0183)	(0.0165)
Log avg. donor capacity	0.1384^{***}	0.1359^{***}
	(0.0278)	(0.0273)
Network exposure (ref.: Marginal projects)		
Hub exposure (top 25%)	0.0734^{**}	
	(0.0260)	
Broker exposure (top 25%)		0.0671^{*}
		(0.0300)
Project type (Core vs. Marginal)		
Core project (Principal + Significant)	-1.4867^{***}	-1.5330^{***}
	(0.0965)	(0.0908)
Interactions		
Exposure × Core	0.0020	0.0345
	(0.0453)	(0.0472)
Year FE	Yes	Yes
Country FE	Yes	Yes
SEs clustered by country	Yes	Yes
Observations	3,972	3,972

Notes: Poisson regression estimates from stacked recipient–year–project-type data. The dependent variable is the number of projects of a given type received by recipient i in year t. Projects are classified using the OECD Rio Marker and collapsed into *Core* projects (Principal and Significant) and *Marginal* projects. Marginal projects serve as the reference category. As a result, the baseline exposure coefficient captures the association between network exposure and the number of marginal projects, while the interaction term indicates whether this association differs for core projects. All covariates are lagged by one year. Standard errors clustered by country are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.17: Unweighted Brokerage

	(2)	(4)
Dependent variable: Project count		
Count brokers (top 25%, unweighted)	0.0097	-0.0496
	(0.0230)	(0.1524)
Count brokers × log GDP per capita		0.0080
		(0.0199)
Country FE	Yes	No
Year FE	Yes	Yes
Observations	1,321	1,324

Notes: These models replicate the main paper specifications for Models 2 and 4 but replace the weighted brokerage measure with an unweighted measure of brokerage, defined as the top quartile of donors by unweighted betweenness centrality in the annual co-financing network. This alternative measure captures whether donors bridge otherwise weakly connected parts of the network regardless of collaboration intensity. The absence of statistically significant main or conditional effects indicates that incidental exposure to bridging donors alone does not increase project allocations.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

References

Agreement, Paris. 2015. Paris agreement. In *report of the conference of the parties to the United Nations framework convention on climate change (21st session, 2015: Paris). Retrived December*. Vol. 4 HeinOnline p. 2.

Alter, K. J. and K. Raustiala. 2018. "The Rise of International Regime Complexity." *Annual Review of Law and Social Sciences* 14.
URL: *https://doi.org/10.1146/annurev-lawsocsci-101317-030830*

Alter, K. J. and S. Meunier. 2009. "Politics of International Regime Complexity." 7(1). n.d.
URL: *https://www.jstor.org/stable/40407209*

Andersen, Thomas Barnebeck, Henrik Hansen and Thomas Markussen. 2006. "US politics and World Bank IDA-lending." *The Journal of Development Studies* 42(5):772–794.

Andonova, Liliana B, Michele M Betsill and Harriet Bulkeley. 2009. "Transnational climate governance." *Global environmental politics* 9(2):52–73.

Avant, Deborah and Oliver Westerwinter, eds. 2016. *The New Power Politics: Networks and Transnational Security Governance*. Oxford University Press.

Bailey, Michael, Anton Strezhnev and Erik Voeten. 2017. "Estimating Dynamic State Preferences from United Nations Voting Data." *Journal of Conflict Resolution* 61(2):430–456.

Barabási, Albert-László and Réka Albert. 1999. "Emergence of Scaling in Random Networks." *Science* 286(5439):509–512.

Barro, Robert J and Jong-Wha Lee. 2005. "IMF programs: Who is chosen and what are the effects?" *Journal of monetary Economics* 52(7):1245–1269.

Bättig, Michèle B and Thomas Bernauer. 2009. "National institutions and global public goods: are democracies more cooperative in climate change policy?" *International organization* 63(2):281–308.

Bellezza, Isabella. 2025. "Networked Trust: Peer Effects, Secrecy, and Cooperation in Global Policing." Revise and Resubmit at the APSR.

Betzold, Carola and Florian Weiler. 2017. "Allocation of aid for adaptation to climate change: Do vulnerable countries receive more support?" *International Environmental Agreements: Politics, Law and Economics* 17:17–36.

Bhattacharya, A, V Songwe, E Soubeyran and N Stern. 2023. "A climate finance framework: decisive action to deliver on the Paris Agreement–Summary." *Second report of the Independent High-Level Expert Group on Climate Finance. London: Grantham Research Institute on Climate Change and the Environment, London School of Economics and Political Science* .

Biermann, Frank, Philipp Pattberg, Harro Van Asselt and Fariborz Zelli. 2009. "The fragmentation of global governance architectures: A framework for analysis." *Global environmental politics* 9(4):14–40.

Bol, Thijs, Mathijs De Vaan and Arnout Van De Rijt. 2018. "The Matthew Effect in Science Funding." *Proceedings of the National Academy of Sciences* 115(19):4887–4890.

Borgatti, Stephen P. 2005. "Centrality and Network Flow." *Social Networks* 27(1):55–71.

Burt, Ronald S. 1992. *Structural Holes: The Social Structure of Competition.* Harvard University Press.

Burt, Ronald S. 2005. *Brokerage and Closure: An Introduction to Social Capital.* Oxford: Oxford University Press.

Carpenter, R. C. 2011. "Vetting the Advocacy Agenda: Network Centrality and the Paradox of Weapons Norms." *International Organization* 65(1):69–102.

Chelminski, Kathryn, Liliana B. Andonova and Yixian Sun. 2022. "Emergence and Structuring of the Clean Energy Regime Complex." *Global Governance* 28(4).

Clark, R. 2022. “Bargain Down or Shop Around? Outside Options and IMF Conditionality.” *The Journal of Politics* 84(3).
URL: *https://doi.org/10.1086/719269*

Clark, Richard T. 2025. *Cooperative Complexity: The Next Level of Global Economic Governance.* Cambridge, United Kingdom: Cambridge University Press.

Cranmer, Skyler J., Bruce A. Desmarais and Justin H. Kirkland. 2012. “Toward a Network Theory of Alliance Formation.” *International Interactions* 38(3):295–324.

Dreher, Axel and Nathan M. Jensen. 2007. “Independent Actor or Agent? An Empirical Analysis of the Impact of U.S. Interests on International Monetary Fund Conditions.” *Journal of Law & Economics* 50(1):105–124.

Drezner, D. W. 2009. “The Power and Peril of International Regime Complexity.” *Perspectives on Politics* 7(1):65–70.

Eilstrup-Sangiovanni, M. 2021. ““Ordering” Global Governance Complexes The Evolution of the Governance Complex for International Civil Aviation.” *The Review of International Organizations* .
URL: *https://doi.org/10.1007/s11558-020-09411-z*

Eilstrup-Sangiovanni, M. and O. Westerwinter. 2022. “The global governance complexity cube: Varieties of institutional complexity in global governance.” *The Review of International Organizations* 17(2):233–262.
URL: *https://doi.org/10.1007/s11558-021-09449-7*

Freeman, Linton C. 1979. “Centrality in Social Networks: Conceptual Clarification.” *Social Networks* 1(3):215–239.

GEF Independent Evaluation Office. 2017. Evaluation of Knowledge Management in the Global Environment Facility. Independent evaluation office briefing Global Environment Facility. Mixed-method evaluation including a meta-analysis of 26 country-level evaluations, benchmarking, interviews, and a country stakeholder survey.

Gehring, T. and B. Faude. 2013. “The Dynamics of Regime Complexes: Microfoundations and Systemic Effects.” 19.
URL: *https://www.jstor.org/stable/24526245*

Green, Jessica F. 2022. "Hierarchy in Regime Complexes: Understanding Authority in Antarctic Governance." *International Studies Quarterly* 66(1).

Hadden, J. and L. Jasny. 2019. "The Power of Peers: How Transnational Advocacy Networks Shape NGO Strategies on Climate Change." *British Journal of Political Science* 49(2):637–659.

Hafner-Burton, Emilie M., Miles Kahler and Alexander H. Montgomery. 2009. "Network Analysis for International Relations." *International Organization* 63(3):559–592.

Heldt, E. C., Henning-C. R. and Fioretos O. 2024. "The Evolution of International Regime Complexes: Theoretical Approaches and Patterns of Adaptation." *The Evolution of International Regime Complexes: Exogenous and Endogenous Transformation* .

Henning, C. R. and T. Pratt. 2023. "Hierarchy and differentiation in international regime complexes: A theoretical framework for comparative research." *Review of International Political Economy* .
URL: *https://doi.org/10.1080/09692290.2023.2259424*

Hoeffler, Anke and Verity Outram. 2011. "Need, merit, or self-interest—what determines the allocation of aid?" *Review of Development Economics* 15(2):237–250.

Kahler, Miles. 2009. *Networked Politics.* Cornell University Press.

Kaya, Ayse and Aslı Leblebicioglu. 2025. "Understanding the World Bank's role in climate finance." *Climatic Change* 178(9):160.

Kaya, Ayse and Aslı Leblebicioğlu. 2024. How Has the World Bank's Climate Finance Changed After the Paris Agreement? Technical report Swarthmore College; CUNY-Baruch.

Keohane, R. O. and D. G. Victor. 2010. "The Regime Complex for Climate Change." *Harvard Project on International Climate Agreements* 34.

Kilby, Christopher. 2013. "An empirical assessment of informal influence in the World Bank." *Economic Development and Cultural Change* 61(2):431–464.

Kilby, Christopher. 2024. Donor motives and aid effectiveness. In *Handbook of Aid and Development*. Edward Elgar Publishing pp. 174–186.

Kinne, Brandon J. 2013. "Network Dynamics and the Evolution of International Cooperation." *The American Political Science Review* 107(4):766–785.

Kinne, Brandon J. 2018. "Defense Cooperation Agreements and the Emergence of a Global Security Network." *International Organization* 72(4):799–837.

Least Developed Countries (LDC) Group. 2024. "Views and recommendations on elements of guidance for the Green Climate Fund." UNFCCC. https://unfccc.int/sites/default/files/resource/LDC_2024_GCF.pdf.

Merton, Robert K. 1968. "The Matthew Effect in Science." *Science* 159(3810):56–63.

Michaelowa, Axel and Katharina Michaelowa. 2011. "Coding error or statistical embellishment? The political economy of reporting climate aid." *World Development* 39(11):2010–2020.

Michaelowa, Katharina and Axel Michaelowa. 2017. "Transnational Climate Governance Initiatives: Designed for Effective Climate Change Mitigation?" *International Interactions* 43(1):129–155.

Obstfeld, David. 2005. "Social Networks, the Tertius Iungens Orientation, and Involvement in Innovation." *Administrative Science Quarterly* 50(1):100–130.

OECD. 2025. "Climate Finance and the USD 100 billion Goal." https://www.oecd.org/en/topics/sub-issues/climate-finance-and-the-usd-100-billion-goal.html. Accessed: 2025-08-14.

Orsini, A., Morin J.-F. and O. Young. 2013. "Regime Complexes: A Buzz, a Boom, or a Boost for Global Governance?" *Global Governance* 19(1):27–39.

Overholt, Maggie, Rhys Gerholdt, Jamal Srouji and Natalia Alayza. 2024. "What Are Nationally Determined Contributions (NDCs) and Why Are They Important?". Accessed: 2024-12-12.
URL: *https://www.wri.org/insights/nationally-determined-contributions-ndcs-explained*

Pratt, Tyler. 2018. "Deference and Hierarchy in International Regime Complexes." *International Organization* 72(3):561–590.

Raustiala, K. and D. G. Victor. 2004. "The Regime Complex for Plant Genetic Resources." *International Organization* 58(2):277–309.

Rawlings, Craig M., Jeffrey A. Smith, James Moody and Daniel A. McFarland. 2023. *Network Analysis: Integrating Social Network Theory, Method, and Application with R.* Cambridge University Press.

Roberts, J Timmons and Romain Weikmans. 2017. "Postface: fragmentation, failing trust and enduring tensions over what counts as climate finance." *International Environmental Agreements: Politics, Law and Economics* 17:129–137.

Roberts, J Timmons, Romain Weikmans, Stacy-ann Robinson, David Ciplet, Mizan Khan and Danielle Falzon. 2021. "Rebooting a failed promise of climate finance." *Nature Climate Change* 11(3):180–182.

Robinson, Stacy-Ann and Matthew Dornan. 2016. "International financing for climate change adaptation in small island developing states." *Regional Environmental Change* 17(4):1–13.

Scholz, John T., Ramiro Berardo and Brad Kile. 2008. "Do Networks Solve Collective Action Problems? Credibility, Search, and Collaboration." *The Journal of Politics* 70(2):393–406.

Seabrooke, Leonard and Lasse Folke Henriksen, eds. 2017. *Professional Networks in Transnational Governance.* Cambridge: Cambridge University Press.

Stadelmann, Martin, Åsa Persson, Izabela Ratajczak-Juszko and Axel Michaelowa. 2014. "Equity and cost-effectiveness of multilateral adaptation finance: Are they friends or foes?" *International Environmental Agreements: Politics, Law and Economics* 14:101–120.

Stone, Randall W. 2004. "The political economy of IMF lending in Africa." *American political science review* 98(4):577–591.

Stone, Randall W. 2008. "The scope of IMF conditionality." *International organization* 62(4):589–620.

Thacker, Strom C. 1999. "The high politics of IMF lending." *World politics* 52(1):38–75.

Toetzke, Malte, Anna Stünzi and Florian Egli. 2022. "Consistent and replicable estimation of bilateral climate finance." *Nature Climate Change* 12(10):897–900.

UNEP. 2022. *Adaptation Gap Report 2022: Too Little, Too Slow Climate: Adaptation Failure Puts World at Risk*. UN.

United Nations. 2010. "Report of the Conference of the Parties on its fifteenth session, held in Copenhagen from 7 to 19 December 2009.". FCCC/CP/2009/11/Add.1.
URL: *https://unfccc.int/resource/docs/2009/cop15/eng/11a01.pdf*

Uzzi, Brian. 1997. "Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness." *Administrative Science Quarterly* 42(1):35–67.

Van de Rijt, Arnout, Idil Afife Akin, Robb Willer and Matthew Feinberg. 2016. "Success-Breeds-Success in Collective Political Behavior: Evidence from a Field Experiment." *Sociological Science* 3:940–950.

Van de Rijt, Arnout, Soong Moon Kang, Michael Restivo and Akshay Patil. 2014. "Field Experiments of Success-Breeds-Success Dynamics." *Proceedings of the National Academy of Sciences* 111(19):6934–6939.

Verdier, D. 2022. "Correction to: Bargaining strategies for governance complex games." *The Review of International Organizations* 17(2):373–373.
URL: *https://doi.org/10.1007/s11558-021-09437-x*

Vreeland, James Raymond. 2019. "Corrupting international organizations." *Annual Review of Political Science* 22(1):205–222.

Vreeland, James Raymond and Axel Dreher. 2014. *The political economy of the United Nations Security Council: Money and influence*. Cambridge University Press.

Wasserman, Stanley and Katherine Faust. 1994. *Social Network Analysis: Methods and Applications*. Cambridge, UK: Cambridge University Press.

Weiler, Florian, Carola Klöck and Matthew Dornan. 2018. "Vulnerability, good governance, or donor interests? The allocation of aid for climate change adaptation." *World Development* 104:65–77.

Widerberg, O. and P. Pattberg. 2016. "Accountability Challenges in the Transnational Regime Complex for Climate Change." *Review of Policy Research* .
URL: *https://doi.org/10.1111/ropr.12217*

World Bank. 2023. "What You Need to Know About How CCDRs Estimate Climate Finance Needs." `https://www.worldbank.org/en/news/feature/2023/03/13/what-you-need-to-know-about-how-ccdrs-estimate-climate-finance-needs`. Accessed July 30, 2025.
URL: *https://www.worldbank.org/en/news/feature/2023/03/13/what-you-need-to-know-about-how-ccdrs-estimate-climate-finance-needs*

Yu, H. and L. Xue. 2019. "Shaping the Evolution of Regime Complex." *Global Governance* 25(4):645–669.