Climate Commitments or Creative Accounting: How International Organizations Navigate Conflicting Demands*

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Abstract

How do international organizations balance competing mandates, like addressing climate change while promoting economic growth? In recent years, the World Bank has pledged to support climate-friendly development while reducing fossil fuel finance. Yet high-profile instances of continued support for oil and gas projects cast doubt on this pledge. We argue that international organizations use multiple strategies to manage conflicting mandates, including bargaining with key principals, engaging in public advocacy to justify programs, and reforming internal procedures to ensure compliance with new priorities while maintaining traditional objectives. We focus on the latter, examining internal procedural reforms related to project classification and expenditure tracking. Using text analysis and statistical models on all World Bank projects approved between 2001 and 2022, we assess the alignment between project descriptions and the Bank's official classifications by sector or theme. Our results show strong agreement for extractive content, but a sharp divergence for climate projects: the official classifications systematically overstate both the climate content of projects and the scale of climate finance. Our findings illustrate how international organizations can alter internal accounting procedures to symbolically reconcile conflicting demands and satisfy multiple constituencies in the face of competing mandates.

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1 Introduction

How do international organizations (IOs) balance competing missions and demands? The World Bank Group currently faces a conflict between its commitment to climate action and its foundational mission to end extreme poverty and boost economic growth. In 2016 and 2020, the Bank adopted increasingly ambitious Climate Change Action Plans, promising to increase climate finance to 35 percent of its total budget and align all its operations with the Paris Agreement. By 2023, it had already become the single largest provider of multilateral climate finance to low- and middle-income countries (European Investment Bank, 2024), and in 2024, it raised its climate finance target to 45 percent.

In parallel, during the 2017 One Planet Summit, the Bank pledged to cease financing upstream oil and gas projects by 2019.[1] However, this pledge has been repeatedly challenged by high-profile instances of continued support for fossil fuel-related activities, leading environmental groups to accuse the Bank of deception.[2] This reflects the complicated mission of IOs, which often must please multiple constituencies (Nielson and Tierney, 2003) and pursue potentially conflicting goals, like decarbonization and development.

For almost three decades, developed country principals have been pushing for increased attention to sustainable development, including programs to address climate change and its effects. At the same time, the Bank's *raison d'être* is to assist the poorest countries. The 2016 Climate Action Plan was spurred by global momentum for climate change mitigation following the Paris Agreement and long-standing pressure from many developed country members. It was also motivated by concerns about how climate change might exacerbate poverty in the developing world through drought, flooding, and other extreme events. Yet, new fossil fuel discoveries promise economic benefits, and helping countries capitalize on benefits is a direct way to promote economic growth. The first Trump Administration's antipathy to the Paris

[1] "Upstream" refers to projects focused on the extraction of natural resources, while "downstream" refers to the management of revenue generated by extraction.

[2] In 2020, for example, Guyana received \$55 million to train oil and gas officials and revamp the banking and insurance sectors to support the fossil fuel industry. See Jasper Jolly. 2020. "Anger Over World Bank's \$55M Pledge to Guyana's Fossil Fuel Industry." *The Guardian*.

Agreement further complicated matters, as the long-standing "gentleman's agreement" that the US chooses the president of the World Bank led to the appointment of David Malpass, a loyalist with similar views on climate change action.[3] After President Biden's inauguration in 2021, the World Bank announced yet another Climate Change Action Plan and restated the intention of aligning climate finance with Paris Agreement goals. Malpass subsequently resigned in 2023 after media attention focused on his previous remarks that appeared to question human-caused climate change.[4] However, US preferences shifted yet again after Donald Trump was re-elected. For instance, in a 2025 speech, US Treasury Secretary Scott Bessent declared: "the Bank must take an all-of-the-above approach to energy that includes financing for gas, oil, and coal ... To accomplish this, the Bank must remove its 45% climate co-benefits financing target, which skews projects away from country priorities and distorts projects away from the goal of increasing access to the affordable and reliable energy needed to increase growth and productivity."[5] Since the US is one of the most important principals of the World Bank, these events illustrate how the Bank is often pulled in multiple directions.

Competing mandates are common for IOs. The International Monetary Fund (IMF) must consider the trade-offs between injecting immediate liquidity to halt debt crises versus requiring painful reforms meant to prevent future crises. The UN Human Rights Council must balance its desire to hold repressive regimes accountable with the universal membership provisions of the UN and the need for engagement with the most repressive regimes, resulting in cases in which states accused of human rights abuses end up serving a term on the Council. The International Criminal Court must contend with its mission to hold perpetrators of war crimes accountable while not unduly infringing on state sovereignty.

We argue that IOs facing potentially competing mandates emanating from multiple principals often adopt strategies to cope. For instance, IOs can bargain with principals to craft compromise solutions that embrace the spirit of demands but allow exceptions. IOs can

[3] Claude Forthomme. 2023. "The Heat Is On: The World Bank Needs To Change," *Impakter*.

[4] BBC News, "David Malpass: World Bank leader who was called climate denier quit," 15 February 2023.

[5] US Department of the Treasury. 2025. *Statement from US Secretary of the Treasury Scott Bessent for the World Bank Development Committee and IMF International Monetary and Financial Committee.*

also engage in public advocacy to promote new programs while continuing pre-existing ones, thereby highlighting efforts to address the demands of some principals without abandoning those of others. Yet another strategy is internal procedural reforms that signal compliance with new goals while allowing traditional programs to continue. While the World Bank has adopted a mixture of these strategies in response to calls for increased climate finance, we focus on the third: internal reforms that allow an IO to come into compliance without completely abandoning other development goals.

Specifically, we delve deeper into project-level data to understand the extent to which the World Bank increased climate finance and reduced oil and gas finance, especially after 2019. Our analysis uses data on all projects funded by the World Bank Group's two public sector institutions: the International Development Association (IDA), which provides concessional loans and grants, and the International Bank for Reconstruction and Development (IBRD), which provides non-concessional loans. To validate the Bank's official project classifications, we use keyword-assisted topic models (Eshima, Imai and Sasaki, 2024) to generate text-based measures of each project's substantive content, assessing how closely these text-derived topics align with the Bank's labels. Then, we examine how both the official classifications and the alternative topics evolved over time, using project-level regressions to compare trends in climate, extractive, and renewable content, with health-related projects as a reference category. Finally, we evaluate whether the Bank's reported climate components translated into meaningful financial commitments by analyzing project-level IDA and IBRD funding. Our results show that while the extractive, renewable, and health measures broadly agree across official and text-based classifications, the climate measures diverge sharply, suggesting that the Bank's reporting systematically overstates both the climate content of its projects and the scale of climate finance they deliver. Overall, the Bank appears to rely on internal reporting adjustments to signal symbolic compliance with climate priorities without substantially shifting its lending practices.

Our main contribution is to highlight how IOs respond to competing goals and interests as well as multiple constituencies. Despite its stated desire to combat climate change, the World Bank must please its principals (whose own climate commitments are often tenuous at best), compete with China (which offers fast, generous infrastructure loans with lax environmental safeguards), promote development in resource-rich countries (where institutions are often too weak to manage windfalls transparently), and fend off accusations of hypocrisy (as it is difficult to demand that recipients downscale emissions when high-emitting donors are unwilling to do the same). It is no surprise, then, that our empirical results suggest the Bank's own accounting appears to overstate its climate commitments: this discrepancy reflects the Bank's need to balance competing missions and please multiple principals with disparate and sometimes rapidly changing interests.

2 Competing Interests in Multilateral Lending

2.1 Principal Demands and Donor Competition

While World Bank lending is ostensibly client-oriented and needs-based (Cormier, 2016), macroeconomic performance is sometimes a secondary consideration when lending to US allies (Kilby, 2009). Important US trade partners or bilateral aid recipients tend to receive larger loans (Fleck and Kilby, 2006), whereas temporary members of the UN Security Council receive IMF loans with fewer conditions (Dreher, Sturm and Vreeland, 2015) and attract more frequent funding from both Bretton Woods institutions (Dreher, Sturm and Vreeland, 2009*a*,*b*). When countries' voting behavior in the UN General Assembly aligns with that of the US, the World Bank tends to disburse loans faster, especially ahead of competitive executive elections (Kersting and Kilby, 2016). Bank staff also tend to design programs compatible with US preferences (Clark and Dolan, 2021). This political control is reinforced by the fact that a considerable chunk of multilateral climate finance comes from multi-donor trust funds (Arias and Clark, 2024), where voluntary contributions allow donors to tie the hands of international bureaucrats and ensure that their own climate preferences are met, even if this comes at the expense of recipients' needs (Reinsberg, 2017; Eichenauer and Reinsberg, 2017; Graham, 2023).

To its credit, the World Bank understands that overly restrictive demands may drive borrowers into the arms of non-traditional lenders, and in the case of China, a geopolitical rival to the US. Faced with competition, the Bank emulates China by funding projects in infrastructure-intensive sectors (including oil and gas) and possibly relaxing environmental safeguard requirements (Zeitz, 2021). It also makes fewer demands to borrowers that simultaneously receive aid from new donors like China, India, Saudi Arabia, and the United Arab Emirates (Hernandez, 2017).

This political reality is compounded by a stark power imbalance. The most powerful members of the Bretton Woods institutions are responsible for the largest share of cumulative carbon emissions. Conversely, those least responsible for such emissions and most vulnerable to climate change have the least decision-making power with these institutions. For example, the US, responsible for a fifth of all cumulative carbon emissions since 1850, controls between 9.71 and 17.66 percent of the votes in the organizations composing the World Bank Group.[6] In contrast, the 68 developing countries that self-identify as climate-vulnerable (V20) are responsible for 5 percent of global emissions and command a similarly small vote share in the World Bank and the IMF (Merling and Forster, 2024, 552).

Given this imbalance, skeptics point to the Bank's so-called organized hypocrisy: its rhetoric changes much faster than its reality (Weaver, 2008). This hypocrisy reflects not only the need for international bureaucrats to please multiple political masters with heterogeneous and inconsistent preferences but also IOs' pathologies and dysfunctions more broadly. If the Bank is beholden to the demands of its key principals and pressured to compete against new donors with less ambitious climate policies, like China (Tørstad, Sælen and Bøyum, 2020), why should it seriously pursue climate change mitigation? The competing pressures to simultaneously meet shifting climate goals of key principals while remaining an influential

[6] As of 2024, the specific US vote shares are 9.71 percent for IDA, 14.81 percent for MIGA, 15.49 percent for IBRD, and 17.66 percent for IFC.

source of development funding are stark.

2.2 Climate Policy

Despite facing pressure from key principals, IOs are ultimately independent actors with their own agendas (Barnett and Finnemore, 1999). IMF staff care about the climate (Clark and Zucker, 2023) and extend less stringent conditions to climate-vulnerable countries (Arias and Clark, 2024). Though there is no equivalent research on the climate preferences of World Bank staff, one can reasonably assume that these individuals agree with their IMF counterparts: not only do both IOs have common development priorities and overlapping operations (Marchesi and Sirtori, 2011), but they also recruit from a similar pool of neoliberal economists (Nelson, 2014).

Additionally, IO staff care about their employer's reputation. Non-governmental organizations can have a meaningful influence on IO behavior (Tallberg et al., 2015); in the past, the World Bank has responded to civil society pressure by dropping large infrastructure projects associated with human rights violations and environmental damage (Wade, 2009). At a minimum, staff want to honor existing commitments to prevent reputational damage. The Bank also seems to respond to new information. Shifts in the World Bank's research program affect the content of loan conditionality; for instance, as staff research increasingly focuses on domestic ownership, more loan conditions reflect this concern (Cormier and Manger, 2022). Lastly, the Bank has remarkable financial autonomy (Nielson and Tierney, 2003). Even after the Executive Board approves specific project loans, staff with country experience and good supervisory ability play a key role in recipient performance (Heinzel and Liese, 2021).

At the leadership level, G-7 countries have become more environmentally concerned, pushing for reforms that increase the Executive Board's involvement in the loan approval process, the reporting requirements for approved projects (with a section devoted to each project's environmental impact), and the number of environmental personnel hired by the

Bank (Nielson and Tierney, 2003). Even if G-7 countries are not willing to reduce their own emissions, they may support such efforts elsewhere — a different type of hypocrisy, but one that would lead to more funding for climate projects in the developing world. And ultimately, even "weak" states can wield outsize influence in international climate negotiations, as their climate vulnerability legitimizes their salient positions (Genovese, 2020).

In summary, World Bank staff are concerned about the environment, want to maintain their reputation, have some discretion over how to distribute loans, and directly influence the implementation of loans. Therefore, we should expect the World Bank to take climate issues seriously: there should be an increase in funding for climate-related initiatives, such as renewable energy and coastal zone management, coinciding with major announcements from the Climate Summit. The pressure to do so has only become worse as extreme climate events have impacted some of the Bank's poorest borrowers.

2.3 Extractive Industries

In financial terms, the volume of extractive industry activity far exceeds that of multilateral lending. In 2023, the World Bank Executive Board approved 322 projects worth \$72.8 *billion*, whereas mineral fuel and oil exports totaled \$1.89 *trillion*.[7] Natural resources are famously associated with rent-seeking behavior (Andersen et al., 2017), reduced incentives to collect taxes (McGuirk, 2013), low democratic accountability (Paler, 2013), fewer women in the labor force (Ross, 2008), and a higher onset of civil war (Ross, 2004).

Still, the extractive sector is a key area of focus for the IMF and the World Bank (Goes and Chapman, 2024; Goes, 2023). This focus is shared by all major IOs, which consistently recommend joining the Extractive Industries Transparency Initiative (EITI), established in 2002 (Sovacool et al., 2016). EITI adherence was historically an informal requirement to reach Heavily Indebted Poor Country (HIPC) status, which would make countries eligi-

[7] World Bank data, reported by the 2023 Annual Report, correspond to fiscal year 2023 (from July 1, 2022 to June 30, 2023). Export data, reported by the UN Comtrade Database for calendar year 2023, correspond to HS Code 27: "mineral fuels, mineral oils and products of their distillation; bituminous substances; mineral waxes."

ble for special assistance from the World Bank and the IMF (David-Barrett and Okamura, 2016). This reflects the international community's emphasis on transparency in the extractive sector. Numerous World Bank projects have funded EITI implementation and related good governance initiatives. This continuous support, despite the mixed evidence of EITI's effectiveness,[8] is rooted in pragmatism: if governed properly, extractive industries can fund development projects, improve infrastructure, and diminish poverty (Venables, 2016), in addition to reducing the need for additional borrowing (Goes and Kaplan, 2024). Abandoning these resources could hinder important development progress.

Even IOs committed to climate action likely understand the realities faced by resource-rich emerging economies, which are not yet diversified enough to turn their backs on the extractive sector. Withdrawing funding or conditioning it on environmental reforms is unlikely to deter these countries from prospecting. Instead, this may simply drive them toward Chinese financing (Zeitz, 2021). If oil and gas projects are to be funded anyway, it might be in the World Bank's best interest to do so directly, ensuring that such projects are managed transparently. The Bank may consider that such projects bring more benefits than costs, at least under some circumstances.

Furthermore, the Bank must navigate a legitimacy crisis. Recipients are increasingly critical of the notion that they should scale back resource production when major donors like Canada, Norway, and the US have increased their own hydrocarbon output in recent years.[9] High-level civil servants across 121 countries already perceive the World Bank and the IMF as biased and ineffective (Heinzel et al., 2020). By making stringent environmental demands that recipients perceive as hypocritical, these institutions risk eroding their authority and reducing compliance with conditionality or policy advice (Weaver, 2008).

[8] For example, EITI has reduced deforestation (Kinda and Thiombiano, 2024) and increased trust in politicians (Fenton Villar, 2020), but it has not increased accountability, political stability, or government effectiveness in compliant countries (Sovacool et al., 2016), though there are benefits at earlier stages of implementation (Papyrakis, Rieger and Gilberthorpe, 2017; Fenton Villar and Papyrakis, 2017).

[9] Jillian Kestler-D'Amours. 2022. "Canada's 'Petro-Provinces' See Opportunity in Russia-Ukraine War." *Al Jazeera*. Sam Meredith. 2023. "Norway's Fossil Fuel Bonanza Stokes Impassioned Debate About How Best to Spend Its 'War Profits.' " *CNBC*. Clifford Krauss. 2023. "Surging US Oil Production Brings Down Prices and Raises Climate Fears." *The New York Times*.

In brief, even if the World Bank is sincerely committed to climate finance, it may continue to finance extractive projects after 2019 due to concerns over pragmatism and legitimacy. Anticipating competition or judging that developmental benefits outweigh climate costs in certain contexts, the Bank may either fund upstream oil and gas projects or provide a separate transparency component for projects already funded by new donors.

2.4 Strategies to Balance Climate and Extractive Demands

The tension between the World Bank's climate rhetoric and its continued support of extractive industries might appear to be an example of organized hypocrisy (Weaver, 2008). Yet we argue that this apparent hypocrisy is, in fact, a necessary institutional survival strategy. The World Bank faces a clear organizational dilemma: it must manage conflicting demands from principals, compete with rival lenders, and maintain institutional legitimacy. Navigating these situations is a normal state of affairs for most IOs. We identify three strategies they pursue in the face of such dilemmas, aiming for symbolic compliance that satisfies external demands while maintaining internal operational stability.

First, IOs bargain directly with principals to craft ambitious goals but retain some operational flexibility. This strategy crafts a compromise solution that is lofty and ambitious, yet soft and flexible. The World Bank has clearly demonstrated this by committing to Paris Agreement goals and eliminating *direct* funding for extractive projects, but strategically reserving the discretion to assist poorer countries with the management of resource revenues. For example, the 2017 pledge to cease funding upstream oil and gas projects by 2019 had an important caveat: "in exceptional circumstances" and "in the poorest countries," the Bank would continue to support initiatives that increased energy access and "strengthen[ed] the transparency, governance, institutional capacity and regulatory environment of their energy sectors — including in oil and gas."[10]

Second, IOs engage in public advocacy and rhetorical shifts to manage external percep-

[10] World Bank Group. 2017. *Q&A: The World Bank Group and Upstream Oil and Gas*. See also: World Bank Group. 2017. *Press Release: World Bank Group Announcements at One Planet Summit.*

tions. This involves strategic publicity campaigns that highlight new programs in response to popular demand. The World Bank's Climate Change Action Plans (2016 and 2020) and related activities served this purpose, highlighting the institutional goal of devoting more attention to sustainable development and climate finance.

Third, and central to our argument, IOs engage in internal procedural reforms that allow for a decoupling between stated goals and actual operations. This decoupling strategy signals concrete progress toward specific goals while preserving flexibility in the organizational lending portfolio. The World Bank provides a clear illustration of this mechanism. Besides pledging to increase climate finance and cease financing upstream oil and gas projects, it changed its project classification and expenditure tracking system in 2016 to account for climate co-benefits, the share of financing dedicated to adaptation or mitigation.[11] According to the Bank's website, "this new taxonomy reflects corporate goals and priorities,"[12] namely, the goal of increasing climate finance to 45 percent of its total budget. We argue that this change in classification served as a functional survival strategy, allowing the Bank to overstate compliance with its climate agenda while obscuring non-compliance. In adopting a new classification, we believe the Bank maximized reported compliance across multiple mandates without a substantial (and potentially conflicting) shift in its lending focus. Specifically, we anticipate that the new classification will systematically overstate the climate content of the Bank's portfolio, while obscuring its ongoing support for extractive industries. This is because the project classifications must be flexible enough to please multiple principals — those that support increased climate funding and those that support increased extractive funding.

[11] World Bank. 2021. "What You Need to Know About Climate Co-Benefits." https://www.worldbank.org/en/news/feature/2021/03/10/what-you-need-to-know-about-climate-co-benefits

[12] https://projects.worldbank.org/en/projects-operations/project-theme

3 Classifying World Bank Projects

To determine how the international organizations respond to competing pressures, we analyze the content of World Bank projects. We begin by describing how the Bank classifies its own projects into *sectors* and *themes*, how these official classifications have evolved over time, and what aspects they may obscure. Next, we conduct a validation exercise using text analysis to produce an alternative classification into *topics* and assess how closely these topics align with the Bank's own sectors and themes. The resulting dependent variables indicate the share of each project associated with a given *sector*, *theme*, or *topic*. Finally, we examine how these classifications have evolved over time, highlighting discrepancies between the official and alternative measures.

3.1 Project Data

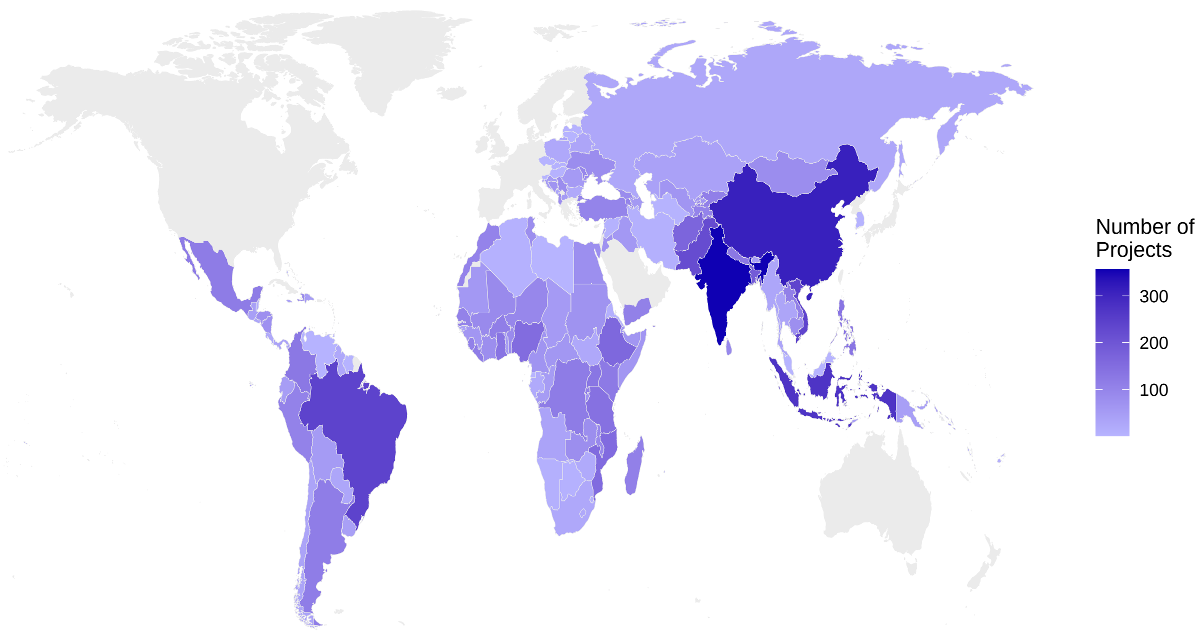
We use data on all projects approved by the World Bank Executive Board from January 2001 to December 2022, excluding projects that cannot be attributed to one single sovereign state or were dropped before securing Executive Board approval.[13] Figure 1 shows the geographic distribution of these projects.

While some of the projects are grants, most fall under one of three lending instruments offered by the World Bank to governments (Heinzel and Liese, 2021). Investment Project Financing (IPF) has a narrow focus: the Bank commits funds to a specific infrastructure project to be implemented by the borrowing government. Development Policy Financing (DPF) has a broader focus on policy reforms and the overall institutional framework. Both IPF and DPF include conditionality, though the former is less specific.[14] To increase bor-

[13]World Bank project information is available since May 1947, but the control variables (discussed in Section 4.2) are not, hence the restricted time frame. In terms of dropped projects, those deemed financially unfeasible may be dropped at the concept review stage, whereas others that fail to meet the Bank's environmental and social requirements may be dropped at the appraisal stage. Only 17 projects were dropped *after* securing Executive Board approval; these are included in the analysis.

[14]Several existing lending instruments were subsumed under the IPF umbrella around 2012: Adaptable Program Loan, Emergency Recovery Loan, Financial Intermediary Loan, Learning and Innovation Loan, Rehabilitation Loan, Sector Investment and Maintenance Loan, Specific Investment Loan, and Technical

Figure 1: Number of Projects by Country, 2001–2022



This map shows the number of projects approved by the World Bank Executive Board, distributed across 150 countries, between 2001 and 2022. This excludes projects that cannot be attributed to one sovereign state or were dropped before securing Executive Board approval. Countries in gray did not receive any projects.

rower ownership and donor coordination, a third instrument, Program-for-Results (P4R), is attached to country-specific outcomes and was rolled out in 2012 (Cormier, 2016). Across all multilateral development banks, IPF, DPF, and P4R accounted for 63, 14, and 6 percent, respectively, of all climate finance provided in 2023 (European Investment Bank, 2024).

3.2 Official Project Taxonomies

The World Bank has two official project taxonomies. The most established taxonomy consists of 11 project *sectors*,[15] ranging from "Agriculture" to "Water/Sanitation/Waste." One of these sectors is "Energy and Extractives;" we use its subsectors to construct our first set

Assistance Loan (World Bank Group, 2012). Other instruments were subsumed under the DPF umbrella: Structural Adjustment Loans, Sector Adjustment Loans, Poverty Reduction Support Credit, and Debt and Debt Service Reduction.

[15] https://projects.worldbank.org/en/projects-operations/project-sector

of dependent variables. The dependent variable *Extractive Sector* captures the percentage of each project that belongs to the subsectors "Mining" or "Oil and Gas." The dependent variable *Renewable Sector* captures the percentage of each project that belongs to the subsectors "Renewable Energy — Biomass," "Renewable Energy — Geothermal," "Renewable Energy — Hydro," "Renewable Energy — Solar," or "Renewable Energy — Wind."[16] For example, the 2011 project "Mozambique Phase II: EITI Implementation" belongs to the subsectors "Oil and Gas" (50 percent) and "Mining" (50 percent). Therefore, the value of *Extractive Sector* for this project is 100 percent, whereas the value of *Renewable Sector* is zero. An additional dependent variable, *Health Sector*, serves as a benchmark, representing a policy area that is largely unrelated to energy and environmental issues but coded under the same taxonomy.

This taxonomy does not have a separate sector for climate-related projects. Recognizing this limitation, the Bank introduced a new taxonomy in July 2016 consisting of eight overlapping project *themes*, including "Environment and Natural Resource Management" and its "Climate Change" sub-theme (level 2). The dependent variable *Climate Theme* captures the percentage of each project belonging to this sub-theme, with *Health Theme* serving as a benchmark (as before). Still, this taxonomy also has an important limitation: it lacks a theme for oil, gas, extractive industries, or non-renewable natural resources. Projects related to these topics often lack a theme or are listed under broader themes. For example, the aforementioned "Mozambique Phase II: EITI Implementation" project falls under the "Public Sector Management" theme, specifically the "Transparency, Accountability, and Good Governance" sub-theme (100 percent). Rather than phasing out upstream oil and gas investments, the World Bank could have simply stopped classifying projects as such. Projects seemingly unrelated to non-renewable natural resources and not labeled as such could still "hide" a natural resource component, allowing the Bank to support the extractive

[16] The remaining subsectors — "Energy Transmission and Distribution," "Non-Renewable Energy Generation," "Other Energy and Extractives," and "Public Administration — Energy and Extractives" — are not specific enough to fall under either category.

sector without violating its pledge to cease direct funding of oil and gas projects. There is no theme for renewable energy either; the sub-theme "Renewable Natural Resources Asset Management" encompasses forests, fisheries, oceans, and biodiversity, whereas the sub-theme "Energy" refers to energy efficiency, access, policies, and reform, without specifying the energy source.

In short, the two official taxonomies are incomplete and often contradictory. A project that generates greenhouse gas emission reductions "using flare gas that would have been otherwise flared" (Russia, 2008) is coded as belonging 100 percent to the oil and gas subsector and 100 percent to the climate sub-theme, illustrating how flexibly each taxonomy can be applied. As an alternative, Zeitz (2021) distinguishes between "hard" sectors (such as water supply, sanitation, transportation, agriculture, mining, and industry) and "soft" sectors (such as health and education). Yet it is difficult to disaggregate the "hard" and "soft" categories, as projects do not always fit neatly into either sector. Since we are interested in one specific "hard" sector for which there may be an incentive to provide erroneous labels, we validate the official classifications using text analysis. This analysis provides an independent measure of the same underlying concept (the project's substantive content), allowing us to test whether the Bank's official sector and theme labels are consistent with what project descriptions actually emphasize.

3.3 Validating the Official Taxonomies

Most projects have a clear title and development objective — say, to "improve management and conservation of important forest ecosystems" (Papua New Guinea, 2001) or "strengthen the capacity of the Federal Government of Somalia to manage its petroleum sector" (Somalia, 2018).[17] We combine each project's title and development objective into one description, translating it into English and correcting typos if necessary. At the preprocessing stage,

[17] Though the World Bank consolidates information about all lending projects into one spreadsheet, sometimes the development objective and lending instrument are missing. In these cases, we scrape the corresponding Project Appraisal Document or Project Performance Assessment Report. When these documents are unavailable, we only work with the project title.

we lowercase all letters and remove punctuation, numbers, separators, and stopwords, but do not stem words to avoid combining words with substantively different meanings (Denny and Spirling, 2018). Finally, we use the preprocessed description to classify projects using Eshima, Imai and Sasaki's (2024) keyword-assisted topic model (keyATM), which captures the relative importance of different topics within a single project and has already been used to classify conditionality from the World Bank (Cormier and Manger, 2022) and the IMF (Goes, 2023).[18] Topic models render this a particularly hard test: in rejecting labels that might align with the Bank's own narrative, the analysis is deliberately biased against the Bank. This sets a higher bar for finding a meaningful result.

The goal of any topic model is to uncover a document's latent themes, or topics, revealing patterns that might not be immediately apparent. The model assumes that each document is a mixture of multiple topics, where each topic is a distribution over words. First, humans pre-specify the number of desired topics. Second, the model assigns words to topics at random. Third, it iteratively refines these assignments based on the likelihood that each word belongs to a topic given its distribution across the entire body of text. Each word can belong to multiple topics. What matters is not just how frequently this word occurs, but how frequently it *co-occurs* with other words. This process continues until the model identifies a set of topics that best explain the word distributions. When identifying a set of topics, the model does not assign documents to topics; rather, it calculates the proportion of each document's vocabulary that corresponds to each topic.

One challenge with traditional topic models like the Latent Dirichlet Allocation model, or LDA (Blei, Ng and Jordan, 2003), is that they heavily depend on human interpretation and can produce topics that are incoherent or difficult to interpret. The top words associated with each topic may not always clearly define a meaningful theme, especially when the documents are short or few — for example, when there are only a few thousand projects consisting of short summaries, as is the case here (Syed and Spruit, 2017). Researchers must

[18]See Appendix B for a detailed model description.

interpret the model output post hoc and manually connect the resulting topics to real-world concepts, a task often akin to "reading tea leaves" (Chang et al., 2009). As a result, topic models may struggle to provide direct answers to specific research questions, returning topics that are neither relevant nor interpretable. Eshima, Imai and Sasaki's keyATM circumvents these issues by allowing researchers to specify topic labels and topic-specific keywords *before* model fitting. These pre-specified labels are ideal for researchers who want to measure specific topics, rather than perform an exploratory analysis. The resulting model yields distinct topics with vocabularies that overlap less. We estimate a dynamic keyATM, which uses a Hidden Markov Model to incorporate time ordering, allowing researchers to investigate how the prevalence of each topic evolves over time.

Table 1: Most Common Words Per Topic

Extractive Topic	Renewable Topic	Climate Topic	Health Topic
eiti	energy	management	**health**
mining	electricity	development	**covid-19**
gas	development	sustainable	response
sector	power	**climate**	services
development	efficiency	conservation	emergency
capacity	access	forest	development
support	increase	environmental	strengthen
implementation	sector	natural	preparedness
oil	improve	biodiversity	support
extractive	**renewable**	areas	improve

Our dynamic keyATM has four pre-specified topics. *Extractive Topic*, *Renewable Topic*, and *Climate Topic* mirror the sectors and themes of interest, whereas the benchmark, *Health Topic*, confirms that the top words associated with each topic define a meaningful theme. Ten residual topics with no keywords absorb content that does not fall under the four topics of interest.[19] Table 1 presents the top ten words for the pre-specified topics. The pre-specified keywords that correctly match the pre-specified topic are in bold. We use the topic proportions as our final dependent variables. These topic-based dependent variables

[19] See Appendix C for a list of keywords and Appendix D for a list of all non-keyword topics, including the most common words per topic.

mirror the official classifications but are generated from text data. The aforementioned project “Mozambique Phase II: EITI Implementation” has the highest value for *Extractive Topic* (99.6 percent), whereas “Rooftop Solar Program for Residential Sector” (Indonesia, 2022) has the highest value for *Renewable Topic* (99.9 percent) and “Regional Disaster Vulnerability Reduction Project” has the highest value for *Climate Topic* (99.9 percent).

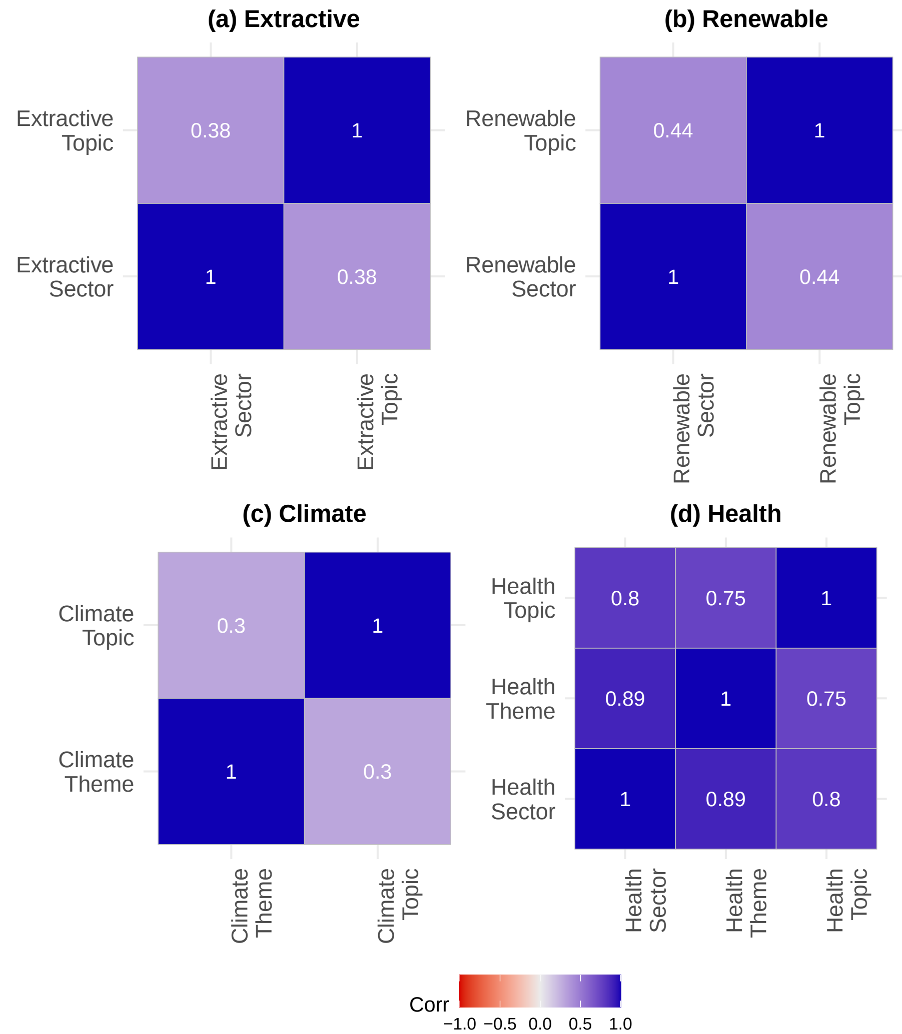
3.4 Dependent Variables

In sum, we have two sets of dependent variables: the official World Bank classifications into sectors (*Extractive Sector* and *Renewable Sector*) or themes (*Climate Theme*); and the text-derived topic proportions (*Extractive Topic*, *Renewable Topic*, and *Climate Topic*). Across all classifications, we use health — a major area in the Bank’s portfolio — as a benchmark category (*Health Sector*, *Health Theme*, and *Health Topic*). Each variable measures the share of a project’s content associated with the respective category, expressed as a proportion between zero and one. For ease of interpretation, we report descriptive figures and predicted values in percentage terms. The alternative text-based classification is not intended to serve as ground truth, as the topic proportions are based on the vocabulary of official project documents rather than on actual project implementation. Still, they provide a way to evaluate how accurately the Bank’s official labels reflect the substantive focus of its projects.

All sectors and themes are positively and significantly correlated with the corresponding topics ($p = 0.000$), indicating that the official and alternative classifications capture related dimensions of project content. However, there is considerable variation across issue areas, as Figure 2 shows. For the benchmark category, the correlations are large, though not perfect (e.g., $r = 0.89$ for *Health Sector* and *Health Theme*).[20] The correlations are considerably smaller for the three issues of interest (e.g., $r = 0.3$ for *Climate Topic* and *Climate Theme*), which may reflect the broader application of the “climate” label to projects with only sec-

[20] Though pre-July 2016 data were retrofitted from sectors to themes, the Bank warns that the two periods (and the two classifications) are not necessarily comparable, as “‘rules of thumb’ were applied to distribute the old data among the new categories (e.g., distributing commitments evenly across sub-themes).”

Figure 2: Correlation Plots



These plots display the correlation between different measurements of a project's (a) extractive, (b) renewable, (c) climate, and (d) health content.

ondary climate relevance. This provides preliminary support for our expectation that the Bank is not changing the types of projects it funds, but rather repackaging its project classification to fit its stated climate ambitions.

4 Explaining Variation in World Bank Projects

4.1 Empirical Strategy

Following prior work (Cormier and Manger 2022; Clark and Dolan 2021; Kersting and Kilby 2016), our unit of analysis is a World Bank project. The key independent variable is time. We aim to understand how project sectors, themes, and topics responded to two historical milestones: the Paris Agreement (2015) and the World Bank's stated end to upstream oil and gas funding (2019). After each critical juncture, we expect a modest decline in extractive content (*Extractive Sector* or *Extractive Topic*), a modest increase in renewable content (*Renewable Sector* or *Renewable Topic*), and a sharper rise in *Climate Theme* — but not necessarily in *Climate Topic*. This divergence reflects the Bank's growing incentive, after 2015 and especially after 2019, to frame projects as climate-related to meet institutional targets for climate finance, even if their actual climate content (as reflected in the text-based classification) did not increase. The prevalence of the benchmark category, health, should be largely unaffected by climate-related policy shifts, instead reflecting events like the Ebola epidemic or the COVID-19 pandemic.

Given the nature of the dependent variables, we estimate fractional logistic regressions that bound predictions within a [0, 1] interval.[21] We model time using a natural cubic spline with three degrees of freedom, placing two internal knots at the two years of interest, 2015 and 2019. This functional form allows for a smooth yet flexible relationship between time and the dependent variables, reflecting gradual changes in project content without imposing strict trends. By placing knots at theoretically meaningful points, the spline can flexibly accommodate shifts around periods of expected change while remaining smooth elsewhere.[22] Following Cormier and Manger (2022), all models include standard errors clustered two ways: by country and by ear. Two-way clustering allows for within-country correlation (as multiple

[21] As a robustness check, we also estimate linear regressions in Appendix G.

[22] In Appendix H, we re-estimate the models using year fixed effects and a simpler specification with an *After 2019* dummy, which captures the average change in project composition following the Bank's 2019 announcement.

projects in one country are often complementary) and within-year correlation (as the World Bank frequently approves similar projects across countries in the same year).

4.2 Control Variables

Beyond temporal dynamics, existing research tends to focus on the number, size, and conditions of World Bank projects, rather than their content. Yet project content is plausibly explained by similar factors: a mix of recipient conditions and donor interests (Cormier and Manger, 2022), all lagged to avoid simultaneity bias.

Good governance affects the types of loans a country receives: poorly governed countries are less likely to receive broad DPF and more likely to receive narrow, project-specific IPF (Winters, 2010). To measure the recipient's quality of governance, we follow Winters (2010) and average all six World Governance Indicators, using linear interpolation when they are unavailable (in 1997, 1999, and 2001). In light of evidence that World Bank lending responds to upcoming elections (Kersting and Kilby, 2016), the dichotomous indicator *Election Year* reflects the occurrence of a presidential or parliamentary election, using data from V-Dem and the Database of Political Institutions (with additional coding for microstates). Models also include dichotomous indicators for *EITI Membership* (from the EITI website), oil and gas *Field Discovery* (from the Global Energy Monitor), *SIDS* (Small Island Developing States, following the official UN classification), and the occurrence of a biological, climatological, meteorological, hydrological, or geophysical *Disaster* (from the International Disasters Database, EM-DAT). Extractive projects might be more prevalent among EITI members. Projects related to climate change or renewable energy might be more prevalent among SIDS (which tend to be more vulnerable to climate change) or in the wake of a drought, wildfire, flood, landslide, or earthquake.

The recipient's logged *Population*, logged *GDP per Capita* (in constant 2015 US dollars), and logged *Resource Rents* (in percentage of the GDP), all from the World Development Indicators 2024, likely affect project content: more populated, poorer countries with large resource wealth may attract more extractive projects, even after 2019. *DAC Aid* indicates the total official development assistance received from members of the Development Assistance Committee (disbursements in billions of constant 2022 US dollars, obtained from the OECD Data Explorer in 2024), whereas *Chinese Finance* (Dreher et al., 2022) indicates the equivalent received from China (new disbursements in billions of constant 2021 US dollars). Though both variables have skewed distributions, we do not log them to avoid losing negative values (which represent loan repayments). Since World Bank lending responds to competition with China (Zeitz, 2021), *Chinese Finance* is crucial for the analysis. However, its coverage is comparatively modest (2000–2022), hence the focus on projects after 2000.

In terms of donor interests, two dichotomous indicators are used: one denotes *IMF Program Participation* (Kentikelenis and Stubbs, 2023) and another denotes *UN Security Council Membership* (Dreher, Sturm and Vreeland, 2009*a*). Using the IMF and UN websites, respectively, we extend the data coverage to 2022. Relatedly, Bailey, Strezhnev and Voeten's (2015) measure of UN General Assembly voting indicates to what extent the recipient's ideal point estimates overlap with those of the US, whose allies receive more projects (Dreher, Sturm and Vreeland, 2009*a*) with fewer conditions (Clark and Dolan, 2021). If the World Bank makes exceptions to its climate commitments, funding oil and gas projects "in exceptional circumstances" even after 2019, US allies may be more likely to fall under this category.

4.3 Explaining Project Content

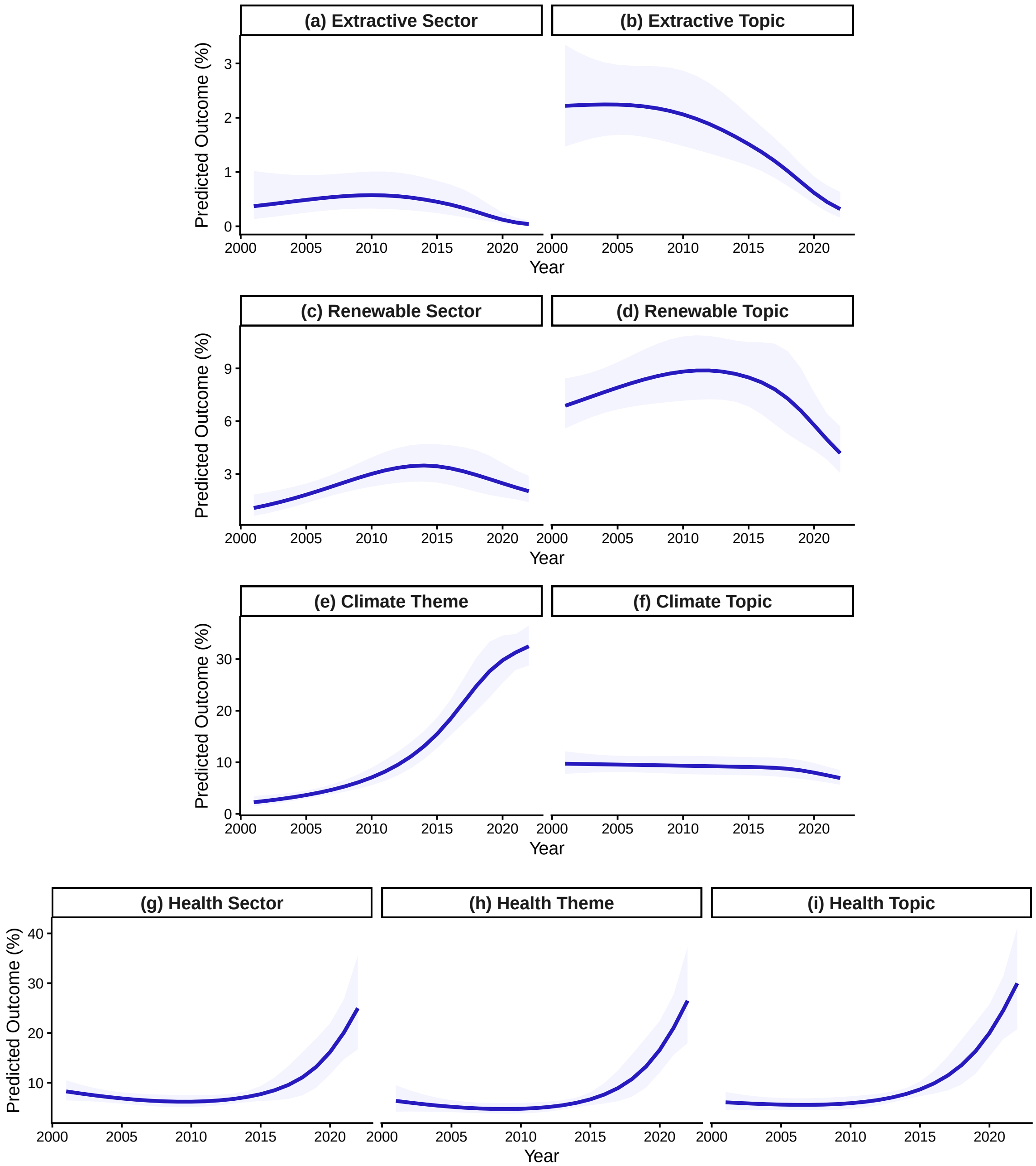
Figure 3 illustrates how the predicted share of World Bank project content related to extractive, renewable, climate, and health issues evolved over time. Each issue area is presented using both the Bank's official classification (into sectors or themes) and the alternative, text-derived classification (into topics). As a reminder, we report the predictions in percentage terms for ease of interpretation, though the fractional logit models use the underlying shares as dependent variables. These predictions are based on models that use natural cubic splines of year, allowing for flexible, nonlinear trends in issue emphasis. Since the spline coefficients themselves are not directly interpretable and the coefficients of control variables are not the substantive focus of this study, we present the full tables only in Appendix F.

In Figure 3, Panels (a) and (b) show that projects coded as extractive (whether by official sector or by topic modeling) peaked around 2010, but approached zero after 2015. This is consistent with the World Bank's gradual withdrawal from direct financing of upstream oil, gas, and mining projects. Though the World Bank promised to stop funding upstream oil and gas *by 2019*, panels (a) and (b) suggest that this was not a strict cut-off, as the Bank was already in the process of doing so. Correspondingly, the pledge to phase out oil and gas funding after 2019 might be akin to "shallow cooperation" (Downs, Rocke and Barsoom, 1996). Panels (c) and (d) display a similar pattern for the sector- and topic-based measures of renewable energy, suggesting that the Bank's portfolio did not shift toward renewable energy investments during this period.

Panels (e) and (f) show the evolution of climate-related projects. The proportion of projects classified under the official climate theme increases sharply after 2015, around the time of the Paris Agreement and the Bank's introduction of its new taxonomy, whereas the topic-based measure remains almost unchanged — indeed, there is a slight decline after 2015. This divergence suggests that the Bank's climate labeling expanded much faster than the actual climate-related content described in project documents, consistent with the hypothesis that there was not an actual increase in climate finance, only an institutional reclassification to fit the Bank's stated priorities. In other words, the Bank might exaggerate the amount of climate funding it provides: although the "climate" label was assigned more generously in recent years, the actual content of projects did not reflect such a change.

To reiterate, the topic proportions rely on the vocabulary of official project documents, not on actual implementation. The broader classification could be correct, and the topic proportions could be incorrect: projects could include a "hidden" climate component despite not explicitly mentioning it in the project summary. If so, panel (e) would paint a more

Figure 3: Predicted Project Content (%)



These panels display the average predicted extractive, renewable, climate, and health content of a project each year. These predictions are based on fractional logistic regressions reported in Appendix F, holding all numeric covariates at their means and categorical covariates at their reference categories. Note that each row has its own y-axis scale.

accurate picture of climate finance than panel (f). However, this is unlikely: given the World Bank's institutional priorities, the official documents should, if anything, *overstate* a project's climate relevance, not obscure it. If a project is in any way related to climate change, the project description should mention it, and the topic proportion should reflect it. The divergence between panels (e) and (f) suggests that recent projects are indeed less climate-centric than the official taxonomy might initially suggest.

Lastly, panels (g), (h), and (i) identify identical trends in health content, consistent with the fact that the three health-related measures (which serve as a validation benchmark) are highly correlated (see Figure 2). The prevalence of such projects hovered below 10 percent until 2015, at which point it increased rapidly. The consistency across these panels confirms that the modeling strategy captures genuine variation rather than measurement noise.

As reported in Appendix F, the control variables behave as expected. For example, EITI members are more likely to attract extractive projects, as are countries with a large GDP share coming from resource rents. Those under an IMF agreement are less likely to attract climate projects, perhaps because such agreements often come at the expense of the environment (Forster, Bhandary and Gallagher, 2024). Where governance is high, climate projects tend to be more common and health projects tend to be less common. *Chinese Finance* has no significant effect on any of the outcomes, suggesting that the content of World Bank projects is not responsive to alternative funding sources.

Overall, these results suggest that the Bank may not be prioritizing climate change as strongly as its public commitments imply. We interpret this as a reflection of the Bank's "balancing act:" it must respond to growing public attention to climate change while also pleasing principals who believe that economic development should be the sole institutional priority. As a result, the official classifications likely exaggerate the actual amount of climate finance provided since 2015.

4.4 Explaining Project Commitments

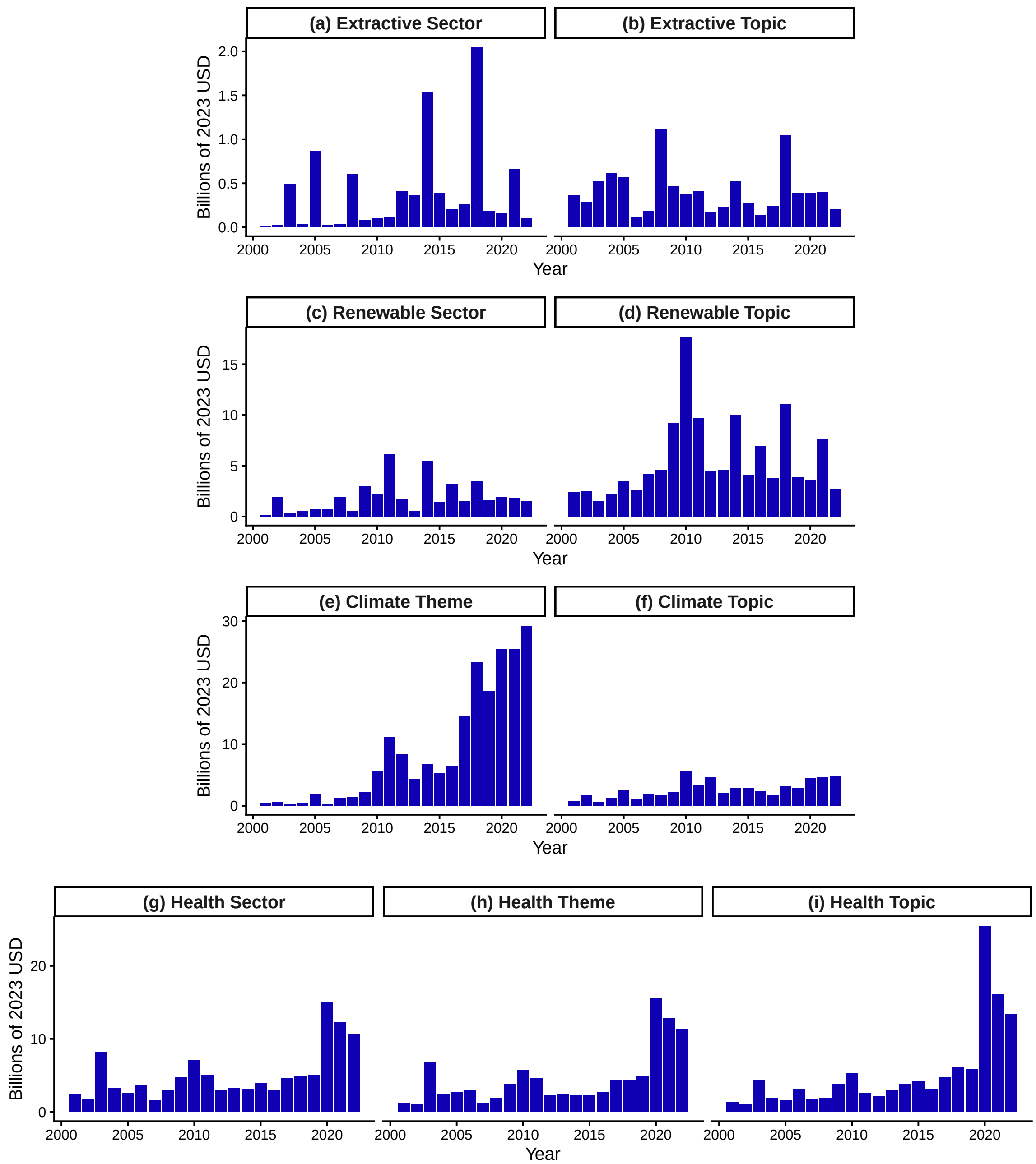
Even if project descriptions do not place greater emphasis on climate finance over time, each climate-related project may mobilize more resources. To test this possibility, we examine new IDA and IBRD commitments at the project level, deflated to constant 2023 USD using the World Development Indicators' GDP deflator. As stated before, the climate theme reflects each project's climate co-benefits, that is, the share of financing explicitly linked to adaptation or mitigation. If a project's IDA and IBRD commitments equal 1,000,000 USD, and 20 percent of this project falls under the climate theme, for instance, the climate co-benefit is equivalent to 200,000 USD. Correspondingly, for each project i, we calculate

$$\text{Climate Theme Commitment}_i = \text{Project Commitment}_i \times \text{Climate Theme Content Share}_i$$

More generally, we calculate the amount of funding directed to each category (*Extractive Sector*, *Extractive Topic*, *Renewable Sector*, and so on) by weighing each project's total commitment by the share devoted to the corresponding category. The resulting variables capture the expected dollar amount going to a given issue area within a project.

We begin by aggregating all projects by year and discussing general trends in the Bank's lending portfolio. Figure 4 presents the estimated annual commitment by category. Each row has its own y-axis scale; while this makes comparisons across rows more difficult, it allows us to visualize within-category variation, especially for smaller issue areas, like extractives. Panels (a) and (b) show that total commitments associated with extractive activities remain small in absolute terms, even if they increased in 2014 and 2018 due to large gas storage projects in Turkey and Egypt. Panels (c) and (d) indicate that renewable projects attracted comparatively larger volumes of finance, peaking around 2010 (when the Bank funded two large power generation and transmission projects in Egypt and Indonesia). Following the theme-based classification, climate-related commitments increased sharply after 2015, reaching nearly 30 billion USD by 2022, as shown in panel (e). This pattern could reflect the Bank's growing integration of climate finance following the Paris Agreement. However, the text-based classification in panel (f) does not mirror this trend. Finally, panels (g), (h), and (i) display a pronounced increase in health-related funding since 2020, consistent with

Figure 4: Total Commitments

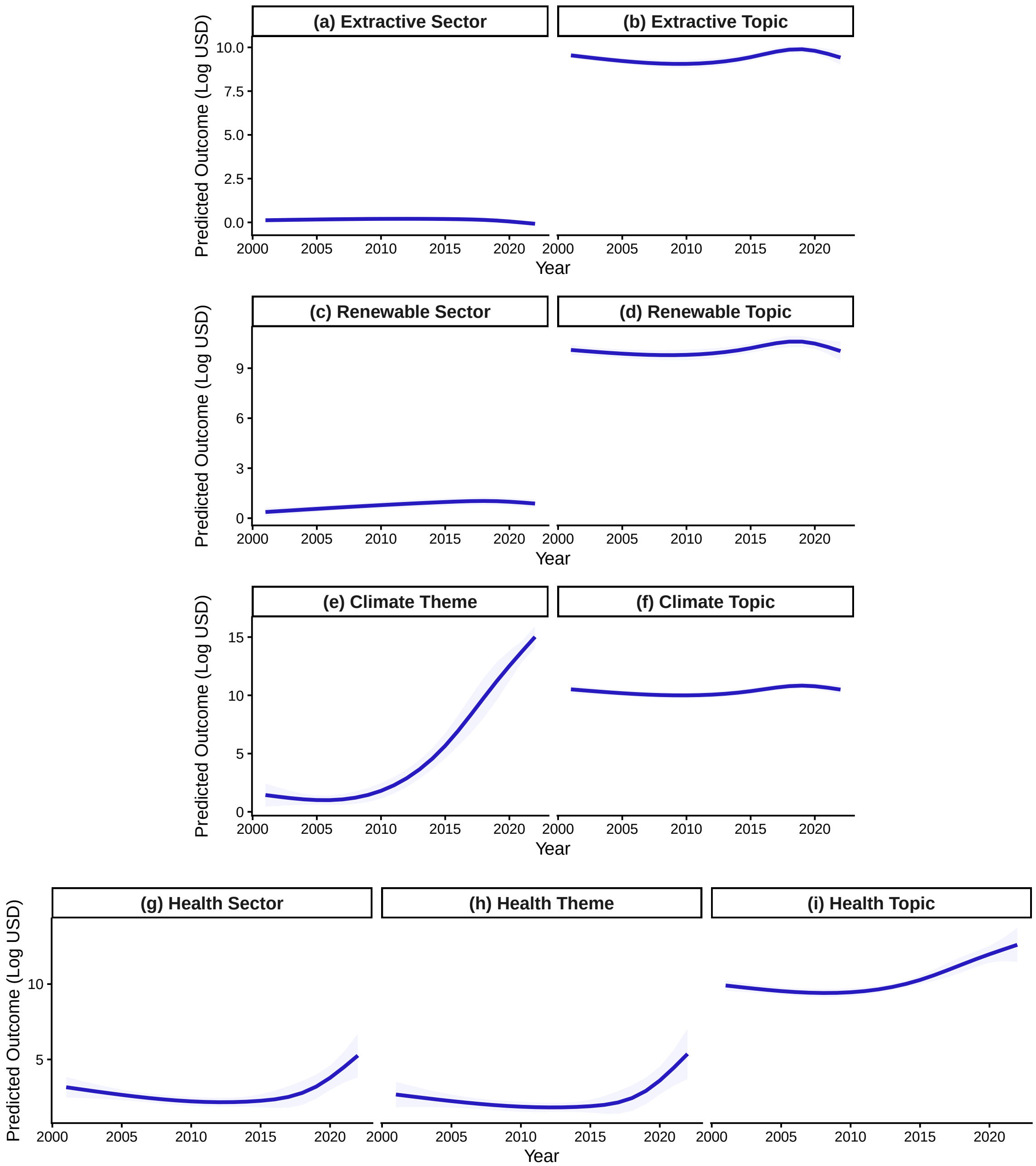


These panels display the total commitment (in billions of 2023 USD) across all projects each year, based on the share of extractive, renewable, climate, and health content. Note that each row has its own y-axis scale.

the surge in health financing during the COVID-19 pandemic, which lends credibility to our variable construction.

While these aggregates provide a clear overview of broad trends, they mask variation

Figure 5: Predicted Project Commitment (Log USD)



These panels display the average predicted new IDA and IBRD commitment (in logged 2023 USD) per project each year, as a function of a project's share of extractive, renewable, climate, and health content. These predictions are based on linear regressions reported in Appendix F, holding all numeric covariates at their means and categorical covariates at their reference categories. Note that each row has its own y-axis scale.

across individual projects. To capture this heterogeneity and allow for formal statistical testing, we next analyze commitments at the project level, considering project-specific characteristics to quantify differences in funding allocation beyond what is apparent in the aggregate figures. In doing so, we log-transform the dollar amounts to ensure that large projects do not skew the analysis. Figure 5 presents the predicted commitments, based on nine linear regressions reported in Appendix F that use spline functions of year and include the same control variables as before.

Figure 5 highlights yet another discrepancy between the Bank's official coding and the alternative topic-based measures. The predicted commitment per project associated with the extractive and renewable *sectors* appears relatively small, as panels (a) and (c) show, but becomes much larger when using the corresponding *topics*; incidentally, panels (b) and (d) are almost identical. Still, these commitments remained almost flat from 2001 to 2022, regardless of the classification. Turning to climate issues, the predicted funding per project increased rapidly when considering the official climate *theme* in panel (e), but remained flat when considering the corresponding climate *topic* in panel (f). The only consistent change over time appears in health-related projects, where both official and alternative measures indicate an increase in new commitments after 2015. Put simply, the Bank allocates a small proportion of its vocabulary to extractive industries (Figure 3), but conditional on recipient characteristics, projects that include some extractive content tend to be as large and capital-intensive as projects in the other three topics of interest (Figure 5).

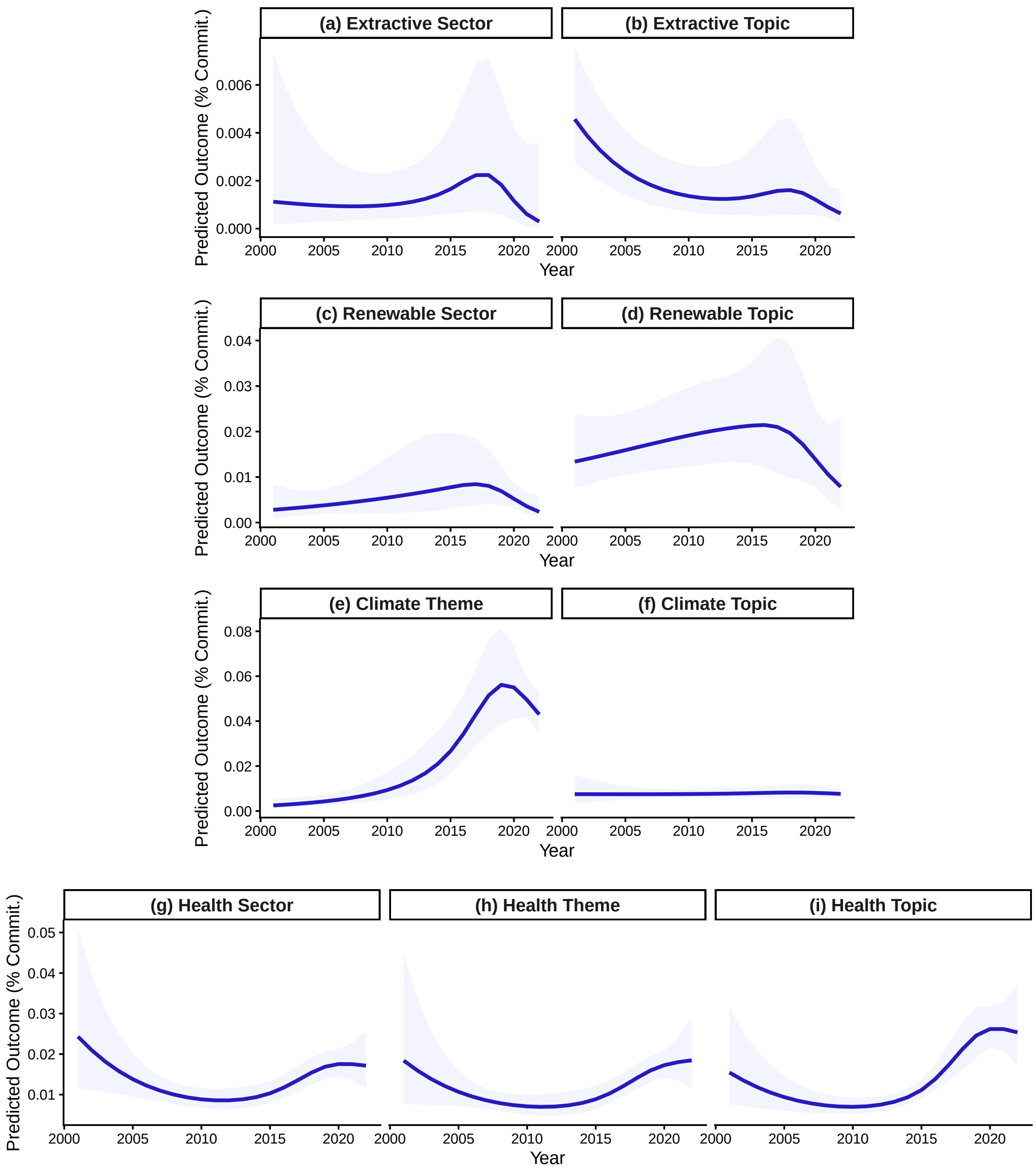
As a final step, we weigh each project's commitment by total new annual IDA and IBRD commitments, taking into account changes in the Bank's overall lending volume.[23] For instance, for each project i and year t, we calculate

$$\text{Climate Theme Funding Share}_i = \frac{\text{Project Commitment}_i \times \text{Climate Theme Content Share}_i}{\text{Total Commitment}_t}$$

We do the same for the remaining sectors, themes, and topics. This adjustment allows us

[23]The IMF has a formal quota system that determines how much member countries can borrow, so IMF studies tend to examine the total amount committed to each loan divided by the corresponding country's borrowing quota (Copelovitch, 2010; Nelson, 2014; Chwieroth, 2013). This strategy is not feasible in the context of the World Bank, which does not have formal quotas.

Figure 6: Predicted Project Commitment (% of Total Commitments)



These panels display the average predicted new IDA and IBRD commitment (as a percentage of total new annual IDA and IBRD commitments) per project each year, as a function of a project's share of extractive, renewable, climate, and health content. These predictions are based on fractional logistic regressions reported in Appendix F, holding all numeric covariates at their means and categorical covariates at their reference categories. Note that each row has its own y-axis scale.

to determine whether climate-related components account for a larger share of each project's weight within the Bank's annual portfolio, rather than merely reflecting an overall increase in such portfolio. We then estimate fractional logistic regressions; in Figure 6, we convert these shares to percentages for ease of interpretation. Each row has its own y-axis scale, enabling us to visualize variation within categories. Across all categories, the average project accounts for less than one percent of total new IDA and IBRD commitments, which makes sense given the large number of projects the Bank funds each year.

Panel (e) in Figure 6 confirms that the share of each project's funding devoted to the climate theme increased steadily after 2010. This pattern suggests that the Bank was already integrating climate components into its operations before the 2016 Climate Change Action Plan, which pledged to increase climate finance from 21 to 28 percent of total lending. In other words, the Bank's commitment largely codified an existing trend rather than marking a substantive behavioral shift. Although the official climate co-benefits of individual projects increased over time, they remained modest in scale (peaking at about 0.06 percent in 2019) and were not reflected in the alternative classification. The extractive and renewable components of projects followed a similar trajectory, rising until around 2016–2017 and then declining sharply. By contrast, the health panels display a clear increase after 2015 across all three measures (sector, theme, and topic). In sum, climate, extractive, renewable, and even health components represent relatively modest shares of broader lending operations rather than stand-alone investments. Taken together, the close correspondence among the extractive, renewable, and health measures contrasts with the divergence between the climate theme and topic, suggesting that the Bank's classifications overstate the extent of climate finance it provides — both in project content and associated funding.

5 Conclusion

International organizations operate under competing mandates, and the World Bank is no exception. On the one hand, civil society and climate-vulnerable states demand a decisive shift toward climate mitigation and adaptation. On the other hand, principals like the US want the Bank to support traditional development priorities, including energy generation and natural resource extraction. Our analysis shows how the Bank navigates these tensions not only through external signaling or rhetorical commitments, but also through internal procedural reforms. By adjusting how projects are labeled and classified, the Bank can demonstrate responsiveness to climate mandates without fully abandoning activities that remain politically important to key principals. We found important differences between the official World Bank classifications and a classification based on keywords in project descriptions. Our point is not to accuse the Bank of circumventing its commitments through so-called "creative accounting," but rather to shed light on how IOs can adjust their own internal procedures to signal their commitment to and progress toward specific goals.

Multilateral funding represents a series of trade-offs. In a world of limited budgets, the choice for one sector or country is necessarily the choice against another. Explicitly testing these choices is difficult, as IO officials may be reluctant to openly discuss extractive finance when civil society and country principals push them not to provide such finance in the first place. In public narratives, the World Bank has an incentive to emphasize its unconditional commitment to climate and renewable energy funding. As such, our findings are somewhat nuanced — the World Bank appears to have taken concrete steps to reduce emphasis on extractive projects and increase resources devoted to climate adaptation, but this conclusion depends on how climate co-benefits are measured. In some cases, projects that have only a tangential connection to addressing climate change are now labeled as featuring climate co-benefits. This label may be accurate, but it also supports the public relations narrative that the Bank would like its constituencies to observe.

Future research will benefit from case studies of specific projects to better understand IOs' climate norms as well as instances of norm deviation. This approach will allow for a more nuanced understanding of the World Bank's climate policies and their implications for global energy transitions. Our text-based approach may also be employed to assess whether Bank leadership is more inclined to support mitigation finance than adaptation finance; the former provides a global public good by reducing total emissions, whereas the latter only provides localized benefits to recipient countries (Pickering et al., 2015). Finally, future research can distinguish between upstream and downstream finance or turn to IFC projects in the private sector, which have been gradually disclosed in recent years. IOs are prone to policy inertia and status quo bias, so even gradual change can represent significant progress.

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Appendix for
Climate Commitments or Creative Accounting: How International Organizations Navigate Conflicting Demands

November 2025

Contents

A Countries Included in the Analysis

Afghanistan, Albania, Algeria, Angola, Antigua & Barbuda, Argentina, Armenia, Azerbaijan, Bahamas, Bangladesh, Barbados, Belarus, Belize, Benin, Bhutan, Bolivia, Bosnia & Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Cape Verde, Central African Republic, Chad, Chile, China, Colombia, Comoros, Costa Rica, Côte d'Ivoire, Croatia, Czechia, Democratic Republic of the Congo, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Eswatini, Ethiopia, Federated States of Micronesia, Fiji, Gabon, Gambia, Georgia, Ghana, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hungary, India, Indonesia, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kenya, Kiribati, Kyrgyzstan, Laos, Latvia, Lebanon, Lesotho, Liberia, Libya, Lithuania, Madagascar, Malawi, Maldives, Mali, Marshall Islands, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nepal, Nicaragua, Niger, Nigeria, North Macedonia, Pakistan, Palau, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Republic of the Congo, Romania, Russia, Rwanda, Samoa, São Tomé & Príncipe, Senegal, Serbia, Seychelles, Sierra Leone, Slovakia, Slovenia, Solomon Islands, Somalia, South Africa, South Korea, South Sudan, Sri Lanka, St. Kitts & Nevis, St. Lucia, St. Vincent & Grenadines, Sudan, Suriname, Syria, Tajikistan, Tanzania, Thailand, Timor-Leste, Togo, Tonga, Trinidad & Tobago, Tunisia, Turkey, Turkmenistan, Tuvalu, Uganda, Ukraine, Uruguay, Uzbekistan, Vanuatu, Venezuela, Vietnam, Yemen, Zambia, Zimbabwe.

B Topic Model Description

To classify the content of World Bank projects, we use the keyword-assisted topic model (keyATM) developed by Eshima, Imai and Sasaki (2024). Like other topic models, the keyATM assumes that each document d (out of a total of D documents) contains N_d words, out of a total of V unique words, which in turn belong to K topics. We can observe the words, but not the topics: they are latent, and the goal of the model is to identify the distribution of the latent topics underlying each document.

Unlike other topic models, the keyATM allows us to distinguish between keyword topics, $\tilde{K}$, and no-keyword topics, $K - \tilde{K}$. For each keyword topic k, we provide L_k keywords; the remaining $K - \tilde{K}$ no-keyword topics are "residual" topics that the model identifies on its own. For each word i in document d, each topic $z_{di} \in \{1, 2, ...K\}$ follows a categorical distribution

$$z_{di} \sim \text{Categorical}(\theta_d), \tag{1}$$

where θ_d is a K-dimensional vector, following a Dirichlet distribution with parameter α (discussed below), $\sum_{k=1}^{K} \theta_{dk} = 1$. The value of θ_d is the main outcome of interest: it is a document-topic distribution that represents the relative proportion of each topic for document d. If the sampled topic z_{di} is a no-keyword topic, each word w_{di} is distributed as follows:

$$w_{di}|z_{di} = k \sim \text{Categorical}(\phi_k) \text{ for } k \in \{\tilde{K}+1, \tilde{K}+2, ..., K\}, \tag{2}$$

where ϕ_k is a V-dimensional vector representing the relative frequency of each word within topic z_{di} (Eshima, Imai and Sasaki 2024, 4). If, however, the sampled topic z_{di} is a keyword topic, the distribution of each word w_{di} follows two steps. First, we draw the random variable

$$s_{di}|z_{di} = k \sim \text{Bernoulli}(\pi_k) \text{ for } k \in \{1, 2, ..., \tilde{K}\}, \tag{3}$$

where π_k is the success probability for word w_{di} (that is, the probability that this word will be sampled). Second, if s_{di} equals 0, the word w_{di} is distributed as follows:

$$w_{di}|s_{di}, z_{di} = k \sim \text{Categorical}(\phi_k) \text{ for } k \in \{1, 2, ..., \tilde{K}\}. \tag{4}$$

If s_{di} equals 1, w_{di} is distributed as follows:

$$w_{di}|s_{di}, z_{di} = k \sim \text{Categorical}(\tilde{\phi}_k) \text{ for } k \in \{1, 2, ..., \tilde{K}\}. \tag{5}$$

where $\tilde{\phi}_{z_n}$ is a V-dimensional vector of probabilities for the keyword list V_k. This means that L_k elements (the keywords) have positive values, and the remaining elements in V are 0. A single word w_{di} can belong to multiple topics, since topics are not strictly independent from one another.

The `R` package `keyATM`, developed by Eshima, Imai and Sasaki (2024), uses the following default values:

$$\pi_k \sim \text{Beta}(1, 1) \text{ for } z_n = \{1, 2, ..., \tilde{K}\} \tag{6}$$

$$\phi_k \sim \text{Dirichlet}(0.01) \text{ for } z_n = \{1, 2, ..., \tilde{K}\} \tag{7}$$

$$\tilde{\phi}_k \sim \text{Dirichlet}(0.1) \text{ for } z_n = \{1, 2, ..., \tilde{K}\} \tag{8}$$

$$\theta_d \sim \text{Dirichlet}(\alpha) \text{ for } d = \{1, 2, ..., D\} \tag{9}$$

$$\alpha_k \sim \begin{cases} \text{Gamma}(1, 1) & \text{for } k = \{1, 2, ..., \tilde{K}\} \\ \text{Gamma}(1, 2) & \text{for } k = \{\tilde{K}+1, \tilde{K}+2, ..., K\} \end{cases} \tag{10}$$

As long as sample size is large, the choice of hyperparameters is not important — with the exception of π_{z_n}, which controls the weight of keywords and has a non-informative prior, Beta$(1, 1)$.

Compared to the base keyATM described above, the extension we use — the dynamic keyATM — replaces Equation 10 with the following:

$$\alpha_{rk} \sim \text{Gamma}(1, 1) \text{ for } r = \{1, 2, ..., \tilde{R}\} \text{ and } k = \{1, 2, ..., \tilde{K}\}, \tag{11}$$

where R are total latent discrete states to which each time period belongs. This allows α to vary across states, and thus the topic proportion to vary over time.

C Keywords

We use the following keywords to generate the $\tilde{K} = 4$ topics of interest:

Extractives: oil, gas, petroleum, eiti, coal, extractive, extractives, diesel, fossil, fuel, hydrocarbon, mining, mine, mineral, minerals

Renewables: renewable, renewables, solar, wind, hydropower, hydroelectric, photovoltaics, biomass, geothermal

Climate: climate, ghg, hcfc, methane, carbon, sequestration, atmosphere, greenhouse, unfccc, adaptation, redd

Health: health, healthy, healthcare, hiv, hospital, hospitals, influenza, malaria, vaccine, vaccination, maternal, flu, hivaids, covid-19, polio, care

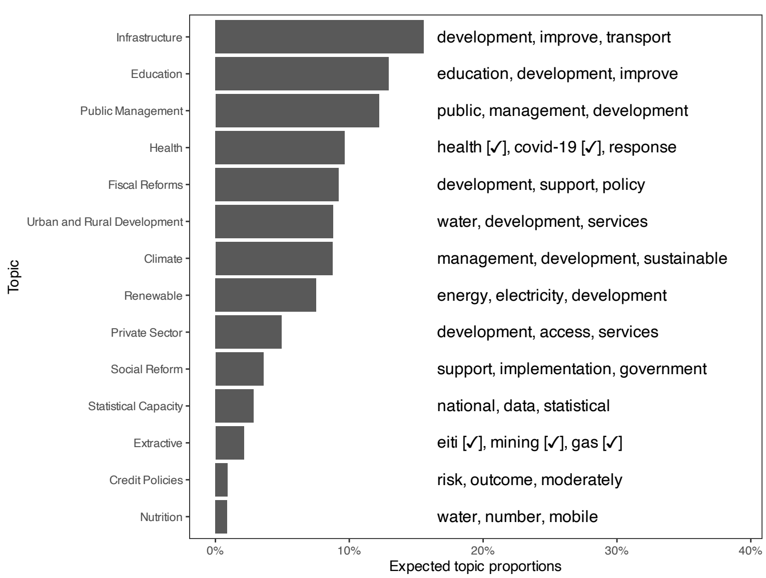
D Additional Topics: Prevalence

Table D.1: Most Common Words Per Topic

Social Reform	Infrastructure	Urban/Rural Development	Nutrition	Public Management
support	development	water	water	public
implementation	improve	development	number	management
government	transport	services	mobile	development
reduction	road	rural	food	sector
poverty	infrastructure	urban	component	financial
country	management	improve	applications	improve
expected	access	sanitation	knowledge	capacity
strategy	emergency	local	expected	strengthening
technical	increase	access	services	support
including	services	supply	supplemental	efficiency

Education	Statistical Capacity	Private Sector	Fiscal Reforms	Credit Policies
education	national	development	development	risk
development	data	access	support	outcome
improve	statistical	services	policy	moderately
social	capacity	land	sector	countries
access	development	capacity	growth	borrower
quality	statistics	improve	public	development
support	new	finance	economic	ratings
services	system	sector	operation	political
poor	support	financial	fiscal	sector
basic	building	enterprises	reforms	credit

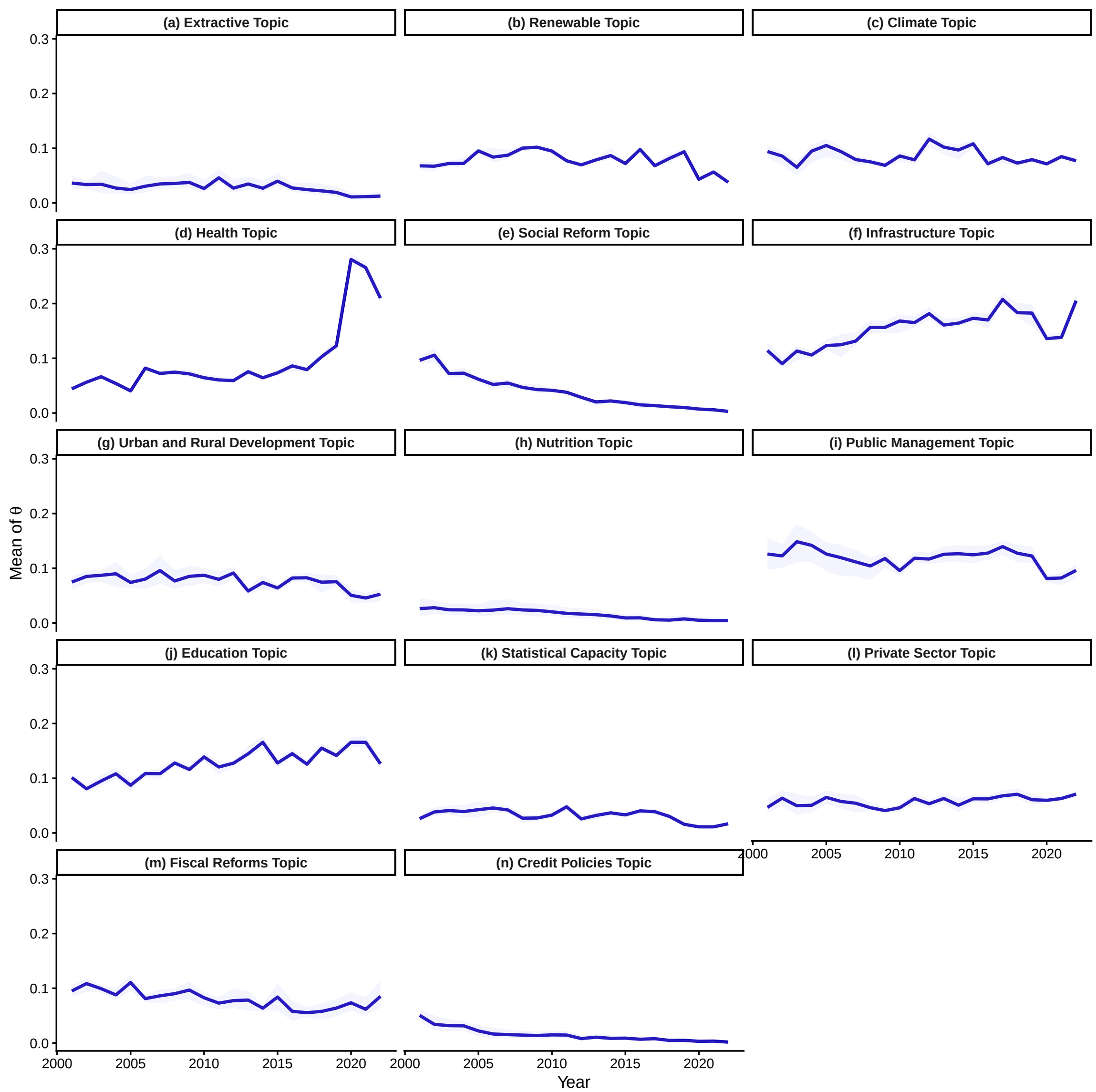
Figure D.1: Expected Proportion of the Corpus, by Topic



This plot displays the expected proportion of the corpus for each topic, with checkmarks representing the keywords used to generate the main topics of interest.

Table D.1 presents the ten most frequent words for all ten non-keyword topics. Although these topics are all "residual" (meaning the model identified them independently, without any researcher input), we assigned post-hoc labels for ease of interpretation. Figure D.1 shows the expected proportion of the corpus belonging to each topic. In Figure D.2, each panel presents θ, the relative prevalence of each topic. The values of θ are averaged for all projects approved by the Executive Board every year between 2001 and 2022.

Figure D.2: Topic Prevalence Over Time, 2001–2022



This plot displays the prevalence of each topic over time. The x-axis represents the year of project approval by the World Bank Executive Board. The y-axis represents θ, the proportion of words in each project description that are associated with a topic, averaged for all projects approved each year, with 90 percent confidence intervals.

E Summary Statistics

Table E.1: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Extractive Sector, Share	9536	0.00819	0.077	0	0	0	1
Extractive Topic, Share	9536	0.0213	0.106	0.00000947	0.000171	0.000393	0.997
Renewable Sector, Share	9536	0.0247	0.137	0	0	0	1
Renewable Topic, Share	9536	0.0752	0.223	0.0000139	0.00018	0.000449	0.999
Climate Theme, Share	9536	0.136	0.278	0	0	0.1	1
Climate Topic, Share	9536	0.0874	0.235	0.00000964	0.000191	0.000523	0.999
Health Sector, Share	9536	0.0884	0.255	0	0	0	1
Health Theme, Share	9536	0.0774	0.235	0	0	0	1
Health Topic, Share	9536	0.0965	0.26	0.00000947	0.00018	0.000483	0.999
Extractive Sector, Log USD	9536	0.185	1.44	-9.75	0	0	16.8
Extractive Topic, Log USD	9536	9.44	2.45	-12.6	7.98	10.8	20.5
Renewable Sector, Log USD	9536	0.536	2.52	0	0	0	17.2
Renewable Topic, Log USD	9536	10	3.34	-12.5	8.01	11.1	23
Climate Theme, Log USD	9536	3.64	5.61	-9.24	0	10.2	16.9
Climate Topic, Log USD	9536	10.2	3.21	-12.5	8.32	11.5	21.9
Health Sector, Log USD	9536	1.93	4.49	0	0	0	17.5
Health Theme, Log USD	9536	1.7	4.29	0	0	0	17.3
Health Topic, Log USD	9536	10.2	3.56	-12.6	8.03	11.4	21.7
Extractive Sector, Share Commit.	9536	0.0000157	0.000408	0	0	0	0.0301
Extractive Topic, Share Commit.	9536	0.000017	0.000208	0	0.0000000493	0.000000803	0.0131
Renewable Sector, Share Commit.	9536	0.0000728	0.000974	0	0	0	0.0426
Renewable Topic, Share Commit.	9536	0.00021	0.00171	0	0.0000000507	0.0000011	0.11
Climate Theme, Share Commit.	9536	0.00029	0.00124	0	0	0.0000365	0.0353
Climate Topic, Share Commit.	9536	0.0000998	0.000752	0	0.0000000694	0.00000155	0.0385
Health Sector, Share Commit.	9536	0.000188	0.00141	0	0	0	0.0957
Health Theme, Share Commit.	9536	0.000162	0.00123	0	0	0	0.0787
Health Topic, Share Commit.	9536	0.00018	0.00113	0	0.0000000528	0.00000146	0.0642
Governance	9536	-0.533	0.507	-2.02	-0.859	-0.215	1.33
Election Year	9536						
... 0	7095	74.4%					
... 1	2441	25.6%					
EITI Member	9536						
... 0	7449	78.1%					
... 1	2087	21.9%					
Field Discovery	9536						
... 0	8155	85.5%					
... 1	1381	14.5%					
SIDS	9536						
... 0	8706	91.3%					
... 1	830	8.7%					
Disaster	9536						
... 0	1874	19.7%					
... 1	7662	80.3%					
Population	9536	16.9	2.02	9.23	15.7	18.2	21.1
GDP per Capita	9536	7.58	0.953	5.53	6.84	8.28	10.4
Resource Rents	9536	1.17	1.59	-6.59	0.354	2.27	4.37
DAC Aid	9536	0.713	1.12	-0.785	0.154	0.977	27.3
Chinese Finance	9536	1.2	4.11	0	0	0.614	65.7
IMF Program	9536						
... 0	5586	58.6%					
... 1	3950	41.4%					
UNSC Member	9536						
... 0	8867	93%					
... 1	669	7%					
Ideal Point Dist.	9536	0.167	0.0897	0	0.109	0.195	0.846

F Main Models

F.1 Explaining Project Content

Table F.1: Predictors of Project Sector, Theme, and Topic, 2001–2022

	(a) Extractive Sector Share	(b) Extractive Topic Share	(c) Renewable Sector Share	(d) Renewable Topic Share	(e) Climate Theme Share	(f) Climate Topic Share	(g) Health Sector Share	(h) Health Theme Share	(i) Health Topic Share
Year (Spline 1)	−0.504	−0.815***	0.609***	−0.041	2.527***	−0.085	0.518	0.825**	1.044***
	(0.388)	(0.211)	(0.225)	(0.225)	(0.202)	(0.103)	(0.322)	(0.346)	(0.305)
Year (Spline 2)	−0.968	−1.568**	2.045***	0.020	4.116***	−0.331	0.519	0.811	1.383***
	(1.046)	(0.609)	(0.623)	(0.238)	(0.536)	(0.262)	(0.347)	(0.532)	(0.395)
Year (Spline 3)	−2.698***	−1.999***	−0.258**	−0.783***	2.251***	−0.336***	1.663***	2.059***	2.055***
	(0.424)	(0.278)	(0.131)	(0.158)	(0.148)	(0.116)	(0.281)	(0.290)	(0.271)
Governance	−0.576**	0.058	0.317	0.142	0.353***	0.465***	−0.274***	−0.360***	−0.439***
	(0.236)	(0.189)	(0.223)	(0.137)	(0.099)	(0.109)	(0.095)	(0.081)	(0.112)
Election Year	0.060	0.168	−0.134	0.031	0.011	−0.163*	−0.068	−0.069	−0.071*
	(0.262)	(0.113)	(0.121)	(0.096)	(0.038)	(0.084)	(0.077)	(0.076)	(0.042)
EITI Member	0.858***	0.917***	−0.253	−0.253*	−0.146*	0.121	−0.049	−0.058	−0.098
	(0.253)	(0.179)	(0.229)	(0.131)	(0.086)	(0.117)	(0.068)	(0.073)	(0.106)
Field Discovery	0.327	0.229	−0.192	−0.146	0.191*	0.086	−0.150	−0.200	−0.208
	(0.412)	(0.180)	(0.224)	(0.149)	(0.109)	(0.099)	(0.162)	(0.169)	(0.143)
SIDS	0.541	0.233	0.227	−0.061	0.577***	0.259	−0.296**	−0.338***	−0.333**
	(0.420)	(0.301)	(0.319)	(0.224)	(0.154)	(0.205)	(0.130)	(0.101)	(0.134)
Disaster	−0.060	0.329**	−0.162	−0.379***	0.056	0.226**	0.102	0.147	0.177
	(0.337)	(0.160)	(0.113)	(0.117)	(0.082)	(0.094)	(0.094)	(0.111)	(0.116)
Population	−0.148	−0.153**	0.066	0.132***	0.152***	0.062	−0.117***	−0.125***	−0.146***
	(0.111)	(0.064)	(0.059)	(0.047)	(0.033)	(0.042)	(0.042)	(0.037)	(0.032)
GDP per Capita	0.346**	−0.039	−0.186**	−0.013	0.075	0.206**	−0.027	0.009	−0.105
	(0.150)	(0.085)	(0.085)	(0.079)	(0.058)	(0.082)	(0.058)	(0.060)	(0.071)
Resource Rents	0.255***	0.093*	−0.028	−0.006	−0.027	0.050	0.032	0.029	−0.008
	(0.094)	(0.052)	(0.064)	(0.036)	(0.023)	(0.037)	(0.022)	(0.020)	(0.024)
DAC Aid	0.025	0.029	0.060	−0.015	−0.093*	−0.090	−0.010	−0.010	−0.032
	(0.035)	(0.050)	(0.053)	(0.029)	(0.049)	(0.065)	(0.019)	(0.027)	(0.040)
Chinese Finance	−0.005	0.016*	−0.012	−0.012	−0.017**	−0.013	0.012*	0.015**	0.009
	(0.022)	(0.008)	(0.014)	(0.008)	(0.008)	(0.009)	(0.007)	(0.006)	(0.008)
IMF Program	0.373*	−0.021	−0.002	−0.098	−0.146***	−0.208**	−0.029	−0.061	0.065
	(0.225)	(0.149)	(0.152)	(0.068)	(0.054)	(0.091)	(0.059)	(0.063)	(0.078)
UNSC Member	0.339	−0.548***	−0.068	−0.231**	0.015	−0.052	0.164	0.189*	0.080
	(0.351)	(0.156)	(0.221)	(0.116)	(0.119)	(0.125)	(0.113)	(0.105)	(0.135)
Ideal Point Dist.	1.189	−0.223	0.138	1.119*	0.062	−0.571	−1.385***	−1.541***	−1.879***
	(1.864)	(0.883)	(1.034)	(0.629)	(0.398)	(0.656)	(0.489)	(0.474)	(0.560)
Intercept	−6.461**	−1.307	−3.919***	−4.447***	−6.658***	−4.704***	−0.293	−0.766	0.455
	(2.690)	(1.239)	(0.980)	(0.895)	(0.732)	(0.799)	(0.756)	(0.718)	(0.621)
Observations	9536	9536	9536	9536	9536	9536	9536	9536	9536
AIC	635.8	1374.9	2041.3	4911.8	5941.1	5364.4	4982.9	4368.8	5324.3
BIC	764.8	1503.8	2170.2	5040.7	6070.0	5493.4	5111.9	4497.8	5453.2

This table presents the results of nine fractional logistic regressions with standard errors clustered by country and year. All independent variables are lagged at $t-1$. The coefficients for natural cubic splines are not directly interpretable on their own; they are used collectively to generate the predicted values shown in the figures. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

F.2 Explaining Project Commitments

Table F.2: Predictors of Project Commitment (Log USD), 2001–2022

	(a) Extractive Sector Log USD	(b) Extractive Topic Log USD	(c) Renewable Sector Log USD	(d) Renewable Topic Log USD	(e) Climate Theme Log USD	(f) Climate Topic Log USD	(g) Health Sector Log USD	(h) Health Theme Log USD	(i) Health Topic Log USD
Year (Spline 1)	0.000	0.854***	0.575***	0.953***	9.896***	0.788***	−0.131	−0.108	1.964***
	(0.082)	(0.178)	(0.110)	(0.275)	(1.130)	(0.171)	(0.552)	(0.613)	(0.400)
Year (Spline 2)	−0.030	−0.709**	1.012***	−0.380	11.016***	−0.686*	0.096	0.697	1.429**
	(0.125)	(0.306)	(0.294)	(0.425)	(1.263)	(0.360)	(0.887)	(1.074)	(0.553)
Year (Spline 3)	−0.276***	0.438**	0.194**	0.330	14.510***	0.562***	2.960***	3.431***	3.369***
	(0.065)	(0.189)	(0.092)	(0.264)	(0.546)	(0.154)	(0.753)	(0.862)	(0.562)
Governance	−0.111	0.036	0.183	0.216	1.105***	0.494***	−0.122	−0.245	−0.305**
	(0.075)	(0.112)	(0.138)	(0.137)	(0.208)	(0.117)	(0.215)	(0.183)	(0.138)
Election Year	0.017	0.029	−0.056	0.071	0.136	−0.161	−0.054	−0.068	0.067
	(0.055)	(0.059)	(0.068)	(0.067)	(0.162)	(0.094)	(0.149)	(0.122)	(0.088)
EITI Member	0.259**	0.161	−0.256*	−0.400**	−0.469	−0.088	−0.244	−0.197	−0.345**
	(0.098)	(0.108)	(0.131)	(0.159)	(0.306)	(0.142)	(0.202)	(0.175)	(0.127)
Field Discovery	0.142	0.064	−0.042	−0.128	0.190	0.164	−0.160	−0.301	−0.108
	(0.105)	(0.123)	(0.140)	(0.152)	(0.369)	(0.137)	(0.251)	(0.219)	(0.144)
SIDS	0.043	−0.029	0.005	−0.211	0.939*	0.202	−0.568*	−0.573**	−0.562**
	(0.079)	(0.174)	(0.208)	(0.151)	(0.518)	(0.244)	(0.274)	(0.263)	(0.206)
Disaster	0.036	0.031	−0.206**	−0.348**	−0.040	0.037	0.267	0.256	0.104
	(0.089)	(0.097)	(0.091)	(0.146)	(0.189)	(0.101)	(0.178)	(0.200)	(0.131)
Population	−0.040**	0.260***	0.061	0.419***	0.435***	0.409***	−0.209***	−0.155***	0.167***
	(0.018)	(0.039)	(0.044)	(0.049)	(0.093)	(0.038)	(0.069)	(0.054)	(0.047)
GDP per Capita	0.050	0.021	−0.176***	0.053	0.173	0.266***	−0.181	−0.097	−0.061
	(0.035)	(0.063)	(0.056)	(0.083)	(0.142)	(0.090)	(0.134)	(0.119)	(0.092)
Resource Rents	0.038***	0.003	0.017	−0.003	−0.013	0.038	0.071	0.020	−0.038
	(0.012)	(0.029)	(0.032)	(0.030)	(0.071)	(0.039)	(0.054)	(0.047)	(0.037)
DAC Aid	0.013	0.059	0.000	0.040	−0.043	0.008	−0.060	−0.076	0.010
	(0.011)	(0.065)	(0.045)	(0.042)	(0.071)	(0.039)	(0.045)	(0.046)	(0.046)
Chinese Finance	0.000	0.012	−0.011	−0.003	−0.042	−0.007	0.030*	0.034**	0.014
	(0.005)	(0.013)	(0.006)	(0.012)	(0.039)	(0.012)	(0.017)	(0.014)	(0.015)
IMF Program	0.092	0.066	−0.054	−0.033	−0.201	−0.124	0.088	0.140	0.129
	(0.054)	(0.079)	(0.080)	(0.088)	(0.165)	(0.108)	(0.136)	(0.109)	(0.109)
UNSC Member	0.034	−0.096	0.023	−0.220*	−0.326	0.009	0.349	0.410**	0.108
	(0.103)	(0.139)	(0.162)	(0.120)	(0.351)	(0.145)	(0.205)	(0.156)	(0.162)
Ideal Point Dist.	−0.177	0.859	0.106	1.651**	−1.597	0.714	−2.468**	−1.945*	−0.335
	(0.292)	(0.628)	(0.662)	(0.718)	(1.463)	(0.636)	(1.025)	(0.981)	(0.685)
Intercept	0.295	4.784***	0.952	2.778**	−6.223***	1.647*	8.061***	5.962***	7.354***
	(0.486)	(0.930)	(0.655)	(1.147)	(2.179)	(0.819)	(1.559)	(1.465)	(1.087)
Observations	9536	9536	9536	9536	9536	9536	9536	9536	9536
R^2	0.007	0.066	0.005	0.063	0.364	0.087	0.021	0.027	0.093

This table presents the results of nine linear regressions with standard errors clustered by country and year. All independent variables are lagged at $t-1$. The coefficients for natural cubic splines are not directly interpretable on their own; they are used collectively to generate the predicted values shown in the figures. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table F.3: Predictors of Project Commitment (Share of Total Commitments), 2001–2022

	(a) Extractive Sector Share Commit.	(b) Extractive Topic Share Commit.	(c) Renewable Sector Share Commit.	(d) Renewable Topic Share Commit.	(e) Climate Theme Share Commit.	(f) Climate Topic Share Commit.	(g) Health Sector Share Commit.	(h) Health Theme Share Commit.	(i) Health Topic Share Commit.
Year (Spline 1)	1.284**	−0.322	1.050*	0.362	2.990***	0.127	0.148	0.330	0.991***
	(0.524)	(0.536)	(0.561)	(0.473)	(0.401)	(0.334)	(0.203)	(0.220)	(0.296)
Year (Spline 2)	−1.002	−3.178***	0.952	0.182	4.218***	0.037	−1.702**	−1.349	−0.710
	(1.896)	(0.448)	(1.698)	(0.734)	(1.003)	(0.819)	(0.861)	(1.127)	(0.703)
Year (Spline 3)	−1.051	−0.886*	−0.662***	−0.821	2.001***	0.027	0.614***	0.935***	1.364***
	(1.249)	(0.502)	(0.226)	(0.532)	(0.242)	(0.167)	(0.206)	(0.242)	(0.254)
Governance	−1.450*	−0.535	0.447	0.193	0.048	0.675***	−0.285	−0.370*	−0.578**
	(0.792)	(0.385)	(0.278)	(0.296)	(0.150)	(0.256)	(0.218)	(0.217)	(0.235)
Election Year	−0.493	−0.370	−0.461	0.269	0.038	0.111	0.087	0.035	−0.013
	(0.538)	(0.293)	(0.295)	(0.209)	(0.102)	(0.207)	(0.087)	(0.104)	(0.127)
EITI Member	−0.642	0.054	−0.806**	−0.422**	0.027	0.220	0.201	0.198	0.173
	(0.534)	(0.318)	(0.370)	(0.187)	(0.140)	(0.137)	(0.171)	(0.172)	(0.176)
Field Discovery	−1.196	0.518	−0.145	−0.553*	−0.055	−0.190	−0.515	−0.584	−0.557*
	(1.066)	(0.460)	(0.442)	(0.317)	(0.194)	(0.199)	(0.335)	(0.378)	(0.286)
SIDS	−1.455**	−0.505	−0.954	−0.915**	−0.251	−0.052	−0.592***	−0.797***	−0.653***
	(0.586)	(0.434)	(0.650)	(0.423)	(0.161)	(0.211)	(0.222)	(0.198)	(0.165)
Disaster	−0.243	0.173	−0.440*	−0.404	0.027	0.337	0.202	0.207	0.206
	(1.118)	(0.376)	(0.249)	(0.289)	(0.168)	(0.214)	(0.194)	(0.190)	(0.177)
Population	0.370**	0.127	0.328***	0.377***	0.317***	0.359***	0.292***	0.292***	0.292***
	(0.169)	(0.093)	(0.070)	(0.069)	(0.031)	(0.024)	(0.061)	(0.058)	(0.054)
GDP per Capita	1.010	0.212	0.173	0.137	0.293***	0.319***	0.345	0.373*	0.214
	(0.618)	(0.302)	(0.182)	(0.162)	(0.061)	(0.091)	(0.225)	(0.210)	(0.192)
Resource Rents	0.016	−0.067	−0.011	0.042	0.016	0.066	−0.010	−0.032	−0.094
	(0.179)	(0.089)	(0.098)	(0.099)	(0.039)	(0.066)	(0.074)	(0.067)	(0.060)
DAC Aid	−0.001	0.032	0.086**	0.036	0.091***	0.057	0.011	0.013	0.015
	(0.125)	(0.073)	(0.037)	(0.045)	(0.034)	(0.045)	(0.053)	(0.047)	(0.054)
Chinese Finance	−0.083	0.013	0.006	0.009	0.001	−0.017	0.001	−0.001	−0.002
	(0.052)	(0.016)	(0.020)	(0.008)	(0.009)	(0.022)	(0.010)	(0.012)	(0.014)
IMF Program	0.347	−0.114	0.558	−0.040	0.008	−0.333**	0.418*	0.437*	0.351**
	(0.301)	(0.228)	(0.428)	(0.215)	(0.128)	(0.134)	(0.232)	(0.236)	(0.171)
UNSC Member	−1.247	−1.108***	0.341	−0.107	0.174	−0.253	0.556***	0.635***	0.501***
	(0.977)	(0.288)	(0.507)	(0.373)	(0.234)	(0.311)	(0.170)	(0.183)	(0.177)
Ideal Point Dist.	3.775	1.368	−0.047	1.434	0.373	0.679	0.474	0.660	−0.064
	(2.582)	(2.590)	(2.611)	(1.494)	(0.879)	(1.469)	(1.136)	(1.234)	(0.859)
Intercept	−26.378***	−14.402***	−16.705***	−16.151***	−18.330***	−18.167***	−16.298***	−16.849***	−15.733***
	(7.387)	(3.475)	(2.174)	(1.819)	(0.968)	(1.022)	(2.213)	(2.087)	(1.815)
Observations	9536	9536	9536	9536	9536	9536	9536	9536	9536
AIC	36.3	36.3	37.4	40.0	41.5	37.9	39.6	39.1	39.4
BIC	165.2	165.3	166.3	168.9	170.5	166.8	168.5	168.0	168.4

This table presents the results of nine fractional logistic regressions with standard errors clustered by country and year. All independent variables are lagged at $t-1$. The coefficients for natural cubic splines are not directly interpretable on their own; they are used collectively to generate the predicted values shown in the figures. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

G Alternative Specifications

G.1 Explaining Project Content With Linear Models

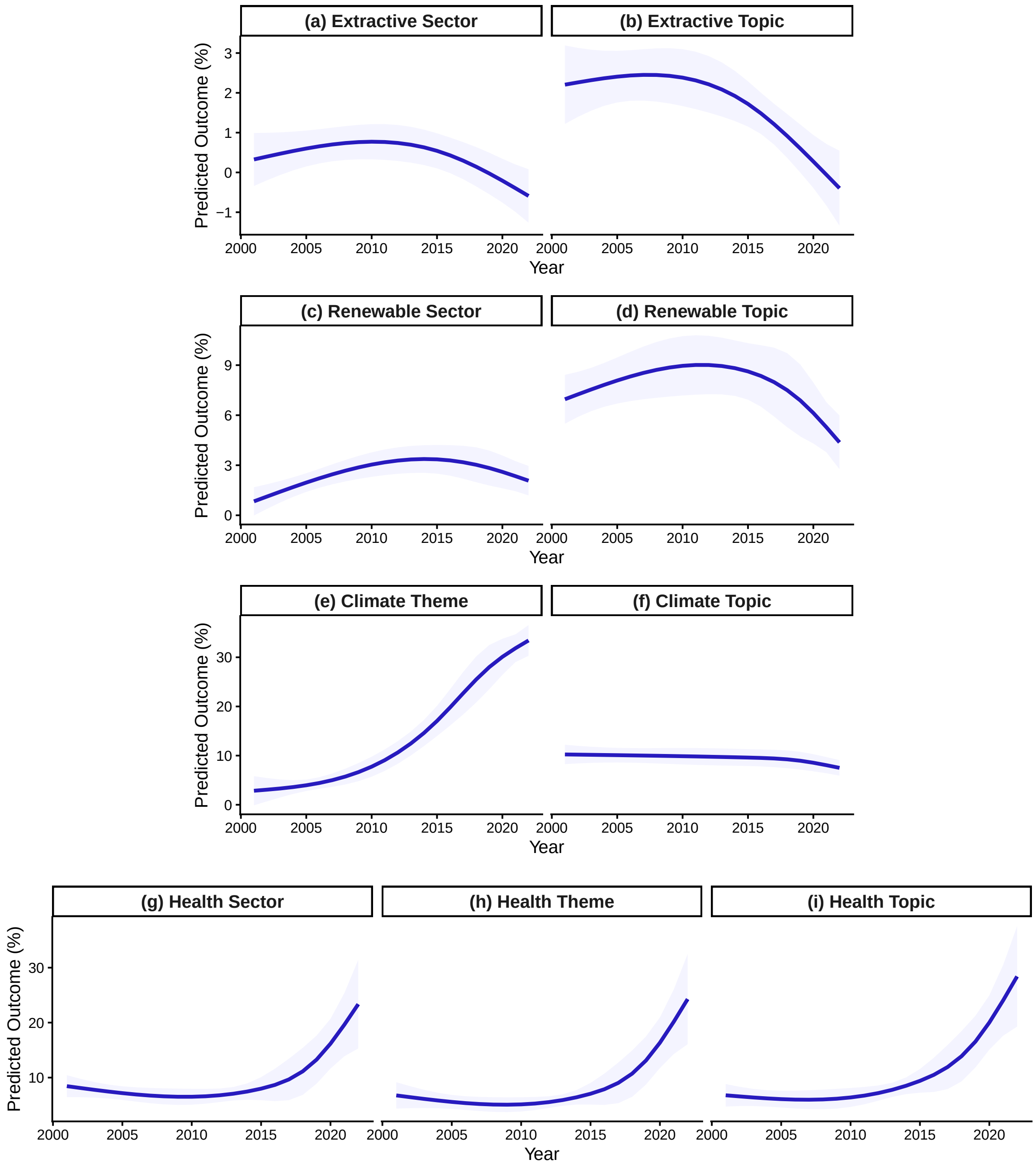
Since the sector, theme, and topic proportions are bounded between 0 and 1, our main empirical approach uses fractional logit regressions. As a robustness check, we also estimate linear regressions for simplicity and interpretability. In doing so, we rescale the dependent variables to percentages (between 0 and 100) to make the coefficients more interpretable and avoid very small numerical values. Table G.1 confirms the main results. One limitation of this alternative approach is that predicted values from a linear regression may occasionally fall slightly outside the [0, 100] range; this occurs in panels (a) and (b) of Figure G.1, which reports the predicted outcomes as percentages — rather than shares — for ease of interpretation.

Table G.1: Predictors of Project Sector, Theme, and Topic, 2001–2022 (Linear Models)

	(a) Extractive Sector %	(b) Extractive Topic %	(c) Renewable Sector %	(d) Renewable Topic %	(e) Climate Theme %	(f) Climate Topic %	(g) Health Sector %	(h) Health Theme %	(i) Health Topic %
Year (Spline 1)	−0.473*	−1.636***	1.339**	−0.360	24.801***	−0.789	3.267	4.515	7.567**
	(0.248)	(0.379)	(0.516)	(1.469)	(2.997)	(0.768)	(2.966)	(2.960)	(3.346)
Year (Spline 2)	−0.041	−1.728	4.204***	1.066	30.995***	−2.507	7.966**	10.344**	15.322***
	(0.657)	(1.189)	(1.055)	(1.609)	(4.032)	(2.056)	(3.449)	(3.829)	(3.943)
Year (Spline 3)	−1.393***	−2.977***	−0.644*	−4.501***	29.193***	−2.496***	17.135***	19.631***	22.966***
	(0.279)	(0.445)	(0.348)	(0.886)	(1.848)	(0.832)	(4.040)	(4.148)	(4.589)
Governance	−0.501**	0.170	0.759	1.049	3.511***	3.559***	−2.195***	−2.527***	−3.750***
	(0.214)	(0.415)	(0.556)	(0.934)	(0.970)	(0.950)	(0.752)	(0.585)	(0.958)
Election Year	0.024	0.279	−0.293	0.259	0.037	−1.218*	−0.470	−0.393	−0.481**
	(0.222)	(0.228)	(0.274)	(0.659)	(0.433)	(0.592)	(0.595)	(0.496)	(0.197)
EITI Member	0.799**	2.040***	−0.644	−1.640**	−2.645**	0.804	−0.517	−0.564	−1.162
	(0.291)	(0.541)	(0.527)	(0.774)	(0.960)	(0.928)	(0.662)	(0.646)	(1.041)
Field Discovery	0.148	0.443	−0.461	−1.121	1.865	1.098	−0.821	−0.956	−0.918
	(0.337)	(0.426)	(0.503)	(1.085)	(1.443)	(1.019)	(1.001)	(0.859)	(0.828)
SIDS	0.510	0.470	0.603	−0.100	6.402***	2.077	−2.361**	−2.447***	−2.981**
	(0.450)	(0.678)	(0.835)	(1.422)	(2.136)	(1.739)	(1.065)	(0.814)	(1.217)
Disaster	−0.120	0.657*	−0.404	−2.670***	0.825	1.752**	0.835	1.074	1.577
	(0.327)	(0.321)	(0.281)	(0.874)	(0.829)	(0.656)	(0.751)	(0.748)	(0.947)
Population	−0.113	−0.295**	0.169	0.975**	1.466***	0.462	−0.879**	−0.835***	−1.165***
	(0.074)	(0.114)	(0.147)	(0.374)	(0.422)	(0.380)	(0.345)	(0.289)	(0.293)
GDP per Capita	0.329***	−0.090	−0.440*	−0.083	1.045	1.799***	−0.192	0.096	−0.748
	(0.114)	(0.187)	(0.215)	(0.548)	(0.617)	(0.623)	(0.457)	(0.418)	(0.565)
Resource Rents	0.193***	0.160	−0.052	−0.032	−0.254	0.396	0.265	0.209	−0.042
	(0.066)	(0.093)	(0.155)	(0.234)	(0.251)	(0.276)	(0.201)	(0.181)	(0.231)
DAC Aid	0.121	0.092	0.165	−0.129	−0.236	−0.336	−0.163	−0.165	−0.370
	(0.088)	(0.158)	(0.202)	(0.180)	(0.349)	(0.223)	(0.165)	(0.215)	(0.257)
Chinese Finance	−0.004	0.039	−0.026	−0.086	−0.197*	−0.118	0.085	0.098**	0.053
	(0.019)	(0.027)	(0.028)	(0.052)	(0.101)	(0.072)	(0.055)	(0.045)	(0.053)
IMF Program	0.286	−0.024	0.001	−0.685	−1.608**	−1.499**	−0.271	−0.459	0.468
	(0.210)	(0.337)	(0.365)	(0.457)	(0.584)	(0.666)	(0.477)	(0.428)	(0.671)
UNSC Member	0.228	−0.918***	−0.141	−1.651*	−0.145	−0.428	1.088	1.059	0.481
	(0.322)	(0.246)	(0.510)	(0.829)	(1.243)	(1.131)	(0.803)	(0.646)	(0.904)
Ideal Point Dist.	0.863	−0.445	0.769	7.927	0.152	−4.267	−9.966**	−9.915**	−14.543**
	(1.661)	(1.760)	(2.474)	(4.635)	(4.311)	(4.840)	(4.376)	(3.759)	(5.520)
Intercept	−0.854	7.076**	1.978	−6.753	−28.119**	−10.427	24.106***	19.124***	31.240***
	(1.924)	(2.583)	(2.289)	(7.036)	(10.027)	(7.285)	(6.436)	(5.613)	(6.061)
Observations	9536	9536	9536	9536	9536	9536	9536	9536	9536
R^2	0.008	0.014	0.004	0.011	0.152	0.024	0.036	0.054	0.070

This table presents the results of nine linear regressions with standard errors clustered by country and year. All independent variables are lagged at $t-1$. The coefficients for natural cubic splines are not directly interpretable on their own; they are used collectively to generate the predicted values shown in the figures. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Figure G.1: Predicted Project Content (%)

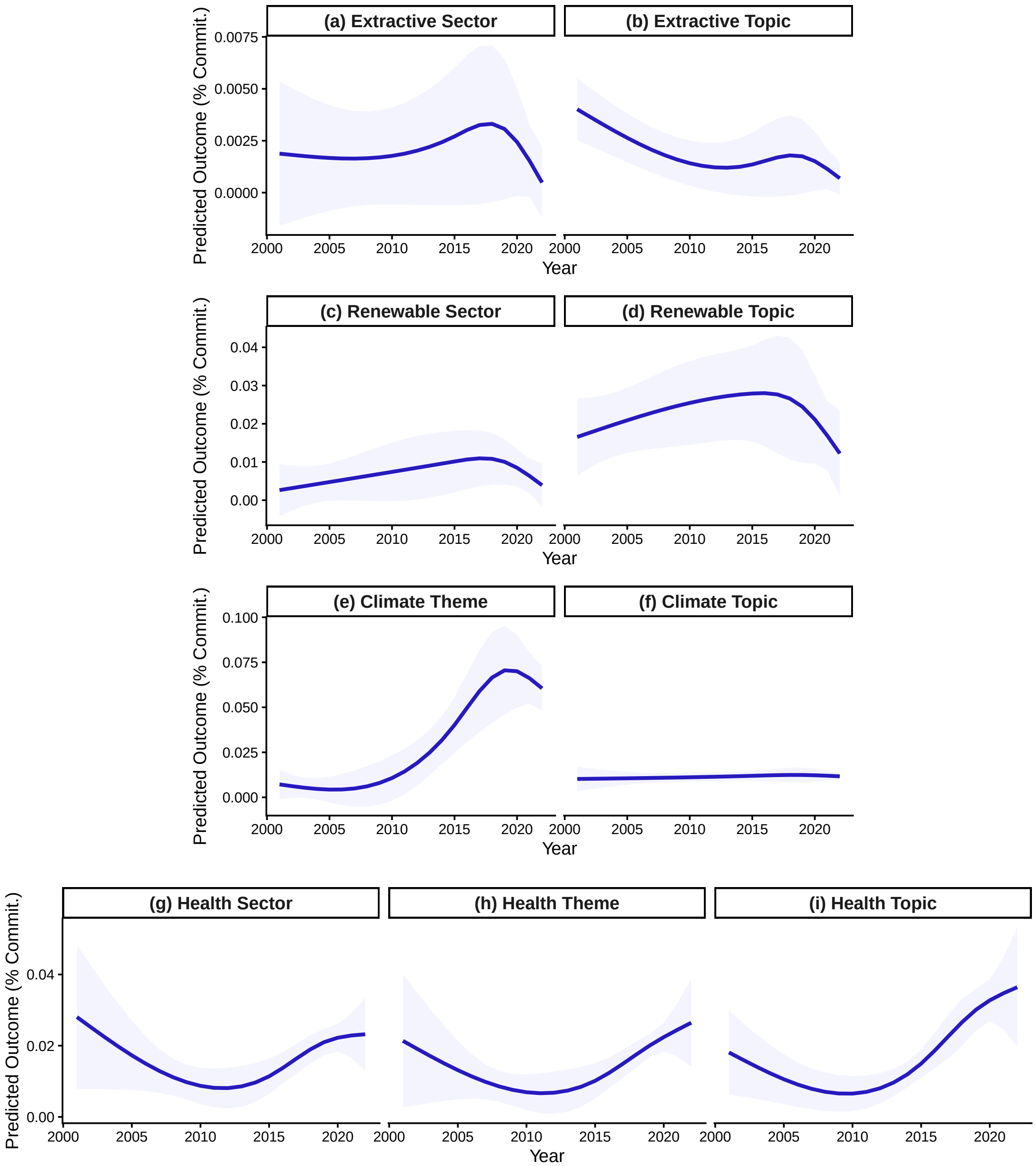


These panels display the average predicted extractive, renewable, climate, and health content of a project each year. These predictions are based on the linear regression models reported in Table G.1, holding all numeric covariates at their means and categorical covariates at their reference categories. Because the estimates are based on linear regression models, some of the predicted values in panels (a) and (b) exceed the [0, 100] bounds. Note that each row has its own y-axis scale.

G.2 Explaining Project Commitments With Linear Models

Although each project's commitment as a share of total new IDA and IBRD commitments is also bounded between 0 and 1, we estimate linear regressions to verify that the main results from fractional logit regressions are robust. As before, we rescale the dependent variables to percentages (between 0 and 100). The results are reported in Table G.2 and the corresponding Figure G.2.

Figure G.2: Predicted Project Commitment (% of Total Commitments)



These panels display the average predicted new IDA and IBRD commitment (as a percentage of total new annual IDA and IBRD commitments) per project each year, as a function of a project's share of extractive, renewable, climate, and health content. These predictions are based on the linear regression models reported in Table G.2, holding all numeric covariates at their means and categorical covariates at their reference categories. Note that each row has its own y-axis scale.

Table G.2: Predictors of Project Commitment (% of Total Commitments), 2001–2022 (Linear Models)

	(a) Extractive Sector % Commit.	(b) Extractive Topic % Commit.	(c) Renewable Sector % Commit.	(d) Renewable Topic % Commit.	(e) Climate Theme % Commit.	(f) Climate Topic % Commit.	(g) Health Sector % Commit.	(h) Health Theme % Commit.	(i) Health Topic % Commit.
Year (Spline 1)	0.002*	−0.001	0.008	0.008	0.076***	0.002	0.002	0.005	0.019***
	(0.001)	(0.001)	(0.005)	(0.010)	(0.017)	(0.003)	(0.005)	(0.004)	(0.006)
Year (Spline 2)	−0.001	−0.006***	0.009	0.011	0.050***	0.003	−0.031	−0.017	−0.002
	(0.003)	(0.001)	(0.011)	(0.013)	(0.015)	(0.007)	(0.023)	(0.023)	(0.014)
Year (Spline 3)	−0.001	−0.001*	−0.002	−0.012*	0.060***	0.001	0.013**	0.019***	0.031***
	(0.001)	(0.000)	(0.002)	(0.007)	(0.008)	(0.002)	(0.005)	(0.006)	(0.009)
Governance	−0.002	−0.001	0.003	0.008	0.005	0.007***	−0.003	−0.004	−0.007
	(0.001)	(0.001)	(0.002)	(0.005)	(0.004)	(0.002)	(0.004)	(0.003)	(0.004)
Election Year	−0.001	−0.001	−0.003	0.005	0.001	0.001	0.001	0.000	−0.001
	(0.001)	(0.000)	(0.002)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
EITI Member	−0.001	0.000	−0.006*	−0.010**	−0.004	0.000	0.003	0.003	0.002
	(0.001)	(0.000)	(0.003)	(0.004)	(0.005)	(0.001)	(0.004)	(0.003)	(0.004)
Field Discovery	−0.002	0.002	−0.001	−0.015*	−0.004	−0.002	−0.010	−0.010	−0.010**
	(0.002)	(0.001)	(0.005)	(0.009)	(0.007)	(0.003)	(0.007)	(0.007)	(0.005)
SIDS	0.000	0.000	0.000	0.006	0.005	0.005**	0.003	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.005)	(0.003)	(0.002)	(0.004)	(0.004)	(0.004)
Disaster	−0.001	0.000	−0.003	−0.009	−0.001	0.001	0.002	0.002	0.002
	(0.002)	(0.000)	(0.002)	(0.005)	(0.003)	(0.001)	(0.003)	(0.002)	(0.002)
Population	0.001	0.000	0.003***	0.009***	0.011***	0.005***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
GDP per Capita	0.002	0.000	0.001	0.002	0.007***	0.003**	0.006	0.006	0.003
	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.005)	(0.004)	(0.004)
Resource Rents	0.000	0.000	0.000	0.001	−0.001	0.000	0.000	0.000	−0.002
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
DAC Aid	0.000	0.000	0.001	0.001	0.002	0.000	0.000	0.000	0.001
	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)	(0.000)	(0.002)	(0.001)	(0.001)
Chinese Finance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IMF Program	0.000	0.000	0.003	−0.002	0.000	−0.003***	0.007	0.006	0.006
	(0.000)	(0.000)	(0.003)	(0.004)	(0.003)	(0.001)	(0.005)	(0.004)	(0.003)
UNSC Member	−0.002	−0.001**	0.003	−0.005	0.003	−0.004	0.016***	0.016***	0.011**
	(0.001)	(0.001)	(0.007)	(0.010)	(0.007)	(0.004)	(0.005)	(0.005)	(0.005)
Ideal Point Dist.	0.006	0.002	0.002	0.027	0.004	0.006	0.009	0.010	−0.003
	(0.009)	(0.004)	(0.014)	(0.027)	(0.022)	(0.011)	(0.017)	(0.017)	(0.013)
Intercept	−0.021	−0.003	−0.046**	−0.146***	−0.229***	−0.086***	−0.114**	−0.106**	−0.095**
	(0.017)	(0.006)	(0.020)	(0.048)	(0.043)	(0.014)	(0.051)	(0.041)	(0.037)
Observations	9536	9536	9536	9536	9536	9536	9536	9536	9536
R^2	0.002	0.004	0.004	0.010	0.072	0.016	0.009	0.011	0.018

This table presents the results of nine linear regressions with standard errors clustered by country and year. All independent variables are lagged at $t-1$. The coefficients for natural cubic splines are not directly interpretable on their own; they are used collectively to generate the predicted values shown in the figures. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

H Alternative Ways to Model Time

H.1 Year Fixed Effects

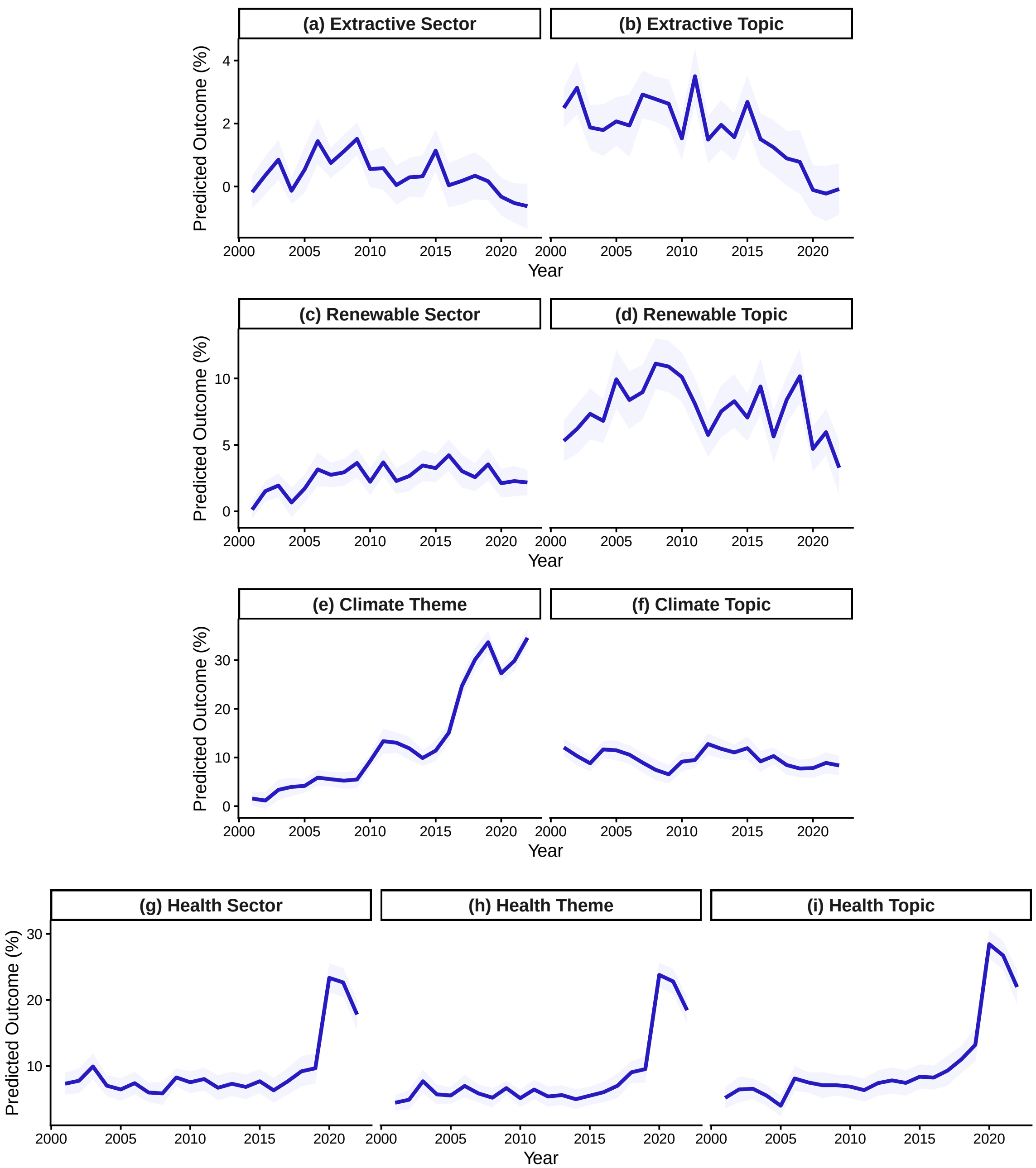
Our main analysis models time using splines, rather than year fixed effects, because we are interested in gradual evolution, not discrete jumps. The World Bank's project portfolio does not change abruptly from one year to the next; it evolves continuously over time. Splines capture this continuous adjustment. In contrast, fixed effects assume unrelated year-by-year shocks, and the inclusion of one fixed effect per year eats degrees of freedom. Still, the results are robust to the use of year fixed effects instead of splines, as Tables H.1 to H.3 (and the corresponding figures) how.

Table H.1: Predictors of Project Sector, Theme, and Topic, 2001–2022 (Year Fixed Effects)

	(a) Extractive Sector Share	(b) Extractive Topic Share	(c) Renewable Sector Share	(d) Renewable Topic Share	(e) Climate Theme Share	(f) Climate Topic Share	(g) Health Sector Share	(h) Health Theme Share	(i) Health Topic Share
Governance	−0.005**	0.001	0.008	0.011	0.034***	0.036***	−0.023***	−0.026***	−0.038***
	(0.002)	(0.004)	(0.006)	(0.010)	(0.010)	(0.010)	(0.008)	(0.006)	(0.010)
Election Year	0.000	0.003	−0.003	0.002	0.000	−0.012*	−0.006	−0.005	−0.006
	(0.002)	(0.003)	(0.003)	(0.007)	(0.005)	(0.006)	(0.007)	(0.006)	(0.004)
EITI Member	0.008**	0.020***	−0.006	−0.016*	−0.024**	0.007	−0.006	−0.005	−0.011
	(0.003)	(0.006)	(0.005)	(0.008)	(0.010)	(0.010)	(0.007)	(0.007)	(0.011)
Field Discovery	0.002	0.004	−0.004	−0.008	0.023	0.009	−0.010	−0.010	−0.010
	(0.003)	(0.005)	(0.006)	(0.012)	(0.015)	(0.012)	(0.011)	(0.009)	(0.010)
SIDS	0.006	0.005	0.007	0.003	0.063***	0.018	−0.022*	−0.021**	−0.026**
	(0.005)	(0.007)	(0.008)	(0.014)	(0.021)	(0.017)	(0.011)	(0.009)	(0.012)
Disaster	−0.002	0.006*	−0.004	−0.029***	0.006	0.019***	0.007	0.009	0.014
	(0.004)	(0.003)	(0.003)	(0.009)	(0.009)	(0.007)	(0.008)	(0.007)	(0.009)
Population	−0.001	−0.003**	0.002	0.011**	0.015***	0.004	−0.008**	−0.008**	−0.011***
	(0.001)	(0.001)	(0.002)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
GDP per Capita	0.003**	−0.001	−0.005*	−0.003	0.010	0.019***	−0.002	0.000	−0.008
	(0.001)	(0.002)	(0.003)	(0.006)	(0.006)	(0.006)	(0.005)	(0.004)	(0.006)
Resource Rents	0.002**	0.002	0.000	0.000	−0.003	0.004	0.004	0.003	0.001
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
DAC Aid	0.001	0.001	0.001	−0.001	−0.003	−0.003	−0.002	−0.002	−0.004
	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)
Chinese Finance	0.000	0.000	0.000	−0.001	−0.002*	−0.001	0.001	0.001	0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
IMF Program	0.003	0.000	0.000	−0.007	−0.017**	−0.015**	−0.003	−0.005	0.005
	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)	(0.005)	(0.005)	(0.007)
UNSC Member	0.002	−0.009***	−0.001	−0.016*	−0.002	−0.006	0.011	0.011*	0.005
	(0.003)	(0.003)	(0.005)	(0.009)	(0.012)	(0.012)	(0.009)	(0.006)	(0.010)
Ideal Point Dist.	0.021	−0.006	0.019	0.151***	0.012	−0.109*	−0.062**	−0.045*	−0.089*
	(0.018)	(0.019)	(0.027)	(0.048)	(0.039)	(0.054)	(0.030)	(0.024)	(0.047)
Intercept	−0.016	0.071**	0.008	−0.091	−0.289***	−0.072	0.214***	0.151***	0.277***
	(0.019)	(0.026)	(0.022)	(0.075)	(0.095)	(0.070)	(0.060)	(0.050)	(0.056)
Observations	9536	9536	9536	9536	9536	9536	9536	9536	9536
AIC	−21 857.4	−15 778.2	−10 784.5	−1660.0	1049.5	−768.5	637.7	−1152.2	614.2
BIC	−21 599.5	−15 520.4	−10 526.6	−1402.1	1307.4	−510.6	895.6	−894.3	872.1

This table presents the results of nine fractional logistic regressions with standard errors clustered by country and year. All independent variables are lagged at $t-1$. The coefficients for year fixed effects are omitted from the table for brevity. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Figure H.1: Predicted Project Content (%, Year Fixed Effects)



These panels display the average predicted extractive, renewable, climate, and health content of a project each year. These predictions are based on fractional logistic regressions reported in Table H.1, holding all numeric covariates at their means and categorical covariates at their reference categories. Note that each row has its own y-axis scale.

Table H.2: Predictors of Project Commitment (Log USD), 2001–2022 (Year Fixed Effects)

	(a) Extractive Sector Log USD	(b) Extractive Topic Log USD	(c) Renewable Sector Log USD	(d) Renewable Topic Log USD	(e) Climate Theme Log USD	(f) Climate Topic Log USD	(g) Health Sector Log USD	(h) Health Theme Log USD	(i) Health Topic Log USD
Governance	−0.109	0.038	0.181	0.224	1.072***	0.506***	−0.127	−0.251	−0.308**
	(0.081)	(0.113)	(0.145)	(0.143)	(0.221)	(0.123)	(0.224)	(0.198)	(0.143)
Election Year	0.017	0.037	−0.068	0.078	0.136	−0.152	−0.072	−0.090	0.061
	(0.059)	(0.061)	(0.079)	(0.079)	(0.168)	(0.093)	(0.175)	(0.152)	(0.092)
EITI Member	0.262**	0.160	−0.241*	−0.389**	−0.358	−0.100	−0.216	−0.157	−0.340**
	(0.107)	(0.131)	(0.137)	(0.169)	(0.307)	(0.162)	(0.208)	(0.194)	(0.153)
Field Discovery	0.145	0.058	−0.016	−0.096	0.353	0.145	−0.170	−0.281	−0.135
	(0.106)	(0.128)	(0.150)	(0.181)	(0.374)	(0.133)	(0.287)	(0.233)	(0.161)
SIDS	0.044	−0.014	0.041	−0.153	0.934*	0.184	−0.495*	−0.460	−0.516**
	(0.083)	(0.181)	(0.210)	(0.161)	(0.497)	(0.241)	(0.282)	(0.275)	(0.207)
Disaster	0.034	0.011	−0.209**	−0.397**	−0.130	0.048	0.223	0.209	0.075
	(0.092)	(0.103)	(0.096)	(0.154)	(0.194)	(0.106)	(0.188)	(0.192)	(0.125)
Population	−0.038*	0.266***	0.068	0.434***	0.440***	0.404***	−0.193***	−0.135**	0.181***
	(0.019)	(0.040)	(0.047)	(0.054)	(0.102)	(0.040)	(0.068)	(0.052)	(0.047)
GDP per Capita	0.046	0.004	−0.185***	0.008	0.135	0.264***	−0.201	−0.124	−0.078
	(0.037)	(0.064)	(0.063)	(0.085)	(0.150)	(0.091)	(0.139)	(0.123)	(0.094)
Resource Rents	0.037**	0.006	0.018	0.005	−0.039	0.040	0.087	0.042	−0.025
	(0.017)	(0.032)	(0.038)	(0.035)	(0.078)	(0.045)	(0.059)	(0.059)	(0.040)
DAC Aid	0.012	0.063	−0.009	0.044	−0.065	0.013	−0.067	−0.094*	0.009
	(0.023)	(0.069)	(0.053)	(0.050)	(0.101)	(0.045)	(0.062)	(0.052)	(0.056)
Chinese Finance	0.001	0.015	−0.011	0.001	−0.044	−0.003	0.033	0.036	0.017
	(0.007)	(0.017)	(0.012)	(0.018)	(0.054)	(0.017)	(0.026)	(0.021)	(0.021)
IMF Program	0.096	0.050	−0.044	−0.053	−0.232	−0.138	0.084	0.127	0.124
	(0.056)	(0.085)	(0.085)	(0.089)	(0.176)	(0.114)	(0.146)	(0.122)	(0.123)
UNSC Member	0.037	−0.093	0.032	−0.221	−0.376	−0.017	0.344	0.412**	0.115
	(0.104)	(0.150)	(0.163)	(0.138)	(0.313)	(0.154)	(0.223)	(0.172)	(0.184)
Ideal Point Dist.	−0.064	1.397**	0.509	2.978***	−0.334	0.498	−1.477*	−0.562	0.580
	(0.307)	(0.660)	(0.725)	(0.770)	(0.954)	(0.708)	(0.834)	(0.837)	(0.721)
Intercept	0.235	4.543***	0.524	2.353*	−6.743***	1.635*	7.112***	4.685***	6.846***
	(0.462)	(0.950)	(0.666)	(1.139)	(2.071)	(0.808)	(1.531)	(1.313)	(1.101)
Observations	9536	9536	9536	9536	9536	9536	9536	9536	9536
R^2	0.009	0.072	0.007	0.070	0.383	0.091	0.028	0.038	0.104

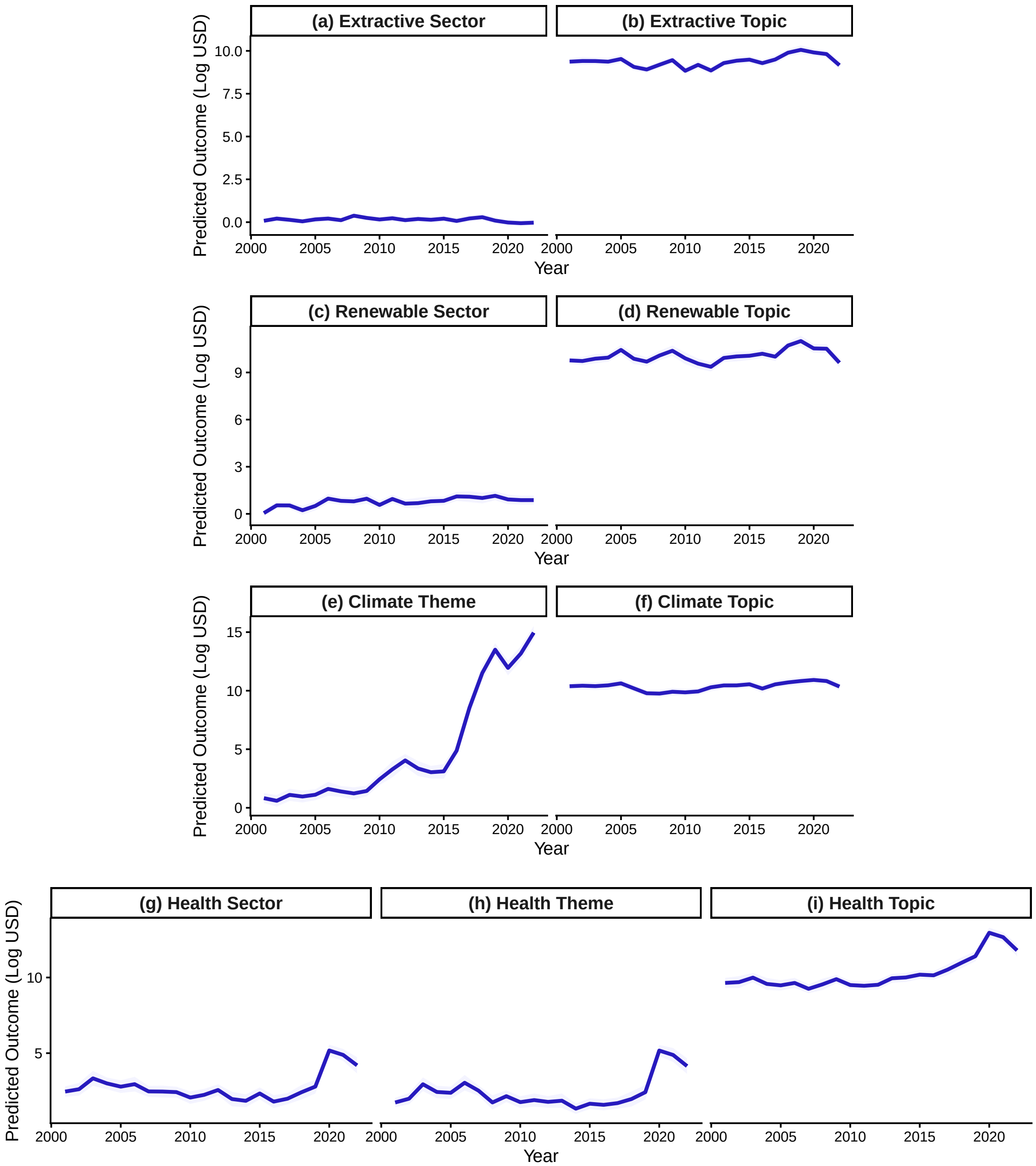
This table presents the results of nine linear regressions with standard errors clustered by country and year. All independent variables are lagged at $t-1$. The coefficients for year fixed effects are omitted from the table for brevity. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table H.3: Predictors of Project Commitment (Share of Total Commitments), 2001–2022 (Year Fixed Effects)

	(a) Extractive Sector Share Commit.	(b) Extractive Topic Share Commit.	(c) Renewable Sector Share Commit.	(d) Renewable Topic Share Commit.	(e) Climate Theme Share Commit.	(f) Climate Topic Share Commit.	(g) Health Sector Share Commit.	(h) Health Theme Share Commit.	(i) Health Topic Share Commit.
Governance	−1.429	−0.503	0.379	0.144	0.046	0.706***	−0.294	−0.382*	−0.596**
	(0.922)	(0.412)	(0.327)	(0.310)	(0.186)	(0.270)	(0.223)	(0.227)	(0.252)
Election Year	−0.362	−0.331	−0.413	0.290	0.095	0.108	0.028	−0.027	−0.065
	(0.472)	(0.297)	(0.350)	(0.223)	(0.112)	(0.244)	(0.139)	(0.157)	(0.148)
EITI Member	−0.712	0.108	−0.847**	−0.470**	0.047	0.204	0.183	0.178	0.172
	(0.562)	(0.363)	(0.405)	(0.227)	(0.176)	(0.173)	(0.185)	(0.195)	(0.204)
Field Discovery	−0.983	0.618	−0.120	−0.528	0.021	−0.127	−0.565	−0.603	−0.588*
	(0.992)	(0.457)	(0.526)	(0.360)	(0.194)	(0.221)	(0.387)	(0.423)	(0.350)
SIDS	−1.437**	−0.414	−0.993	−0.893**	−0.285	−0.102	−0.509**	−0.705***	−0.596***
	(0.589)	(0.465)	(0.662)	(0.436)	(0.186)	(0.229)	(0.260)	(0.252)	(0.185)
Disaster	−0.407	0.086	−0.355	−0.423	−0.010	0.354	0.206	0.210	0.192
	(0.906)	(0.374)	(0.334)	(0.301)	(0.192)	(0.223)	(0.235)	(0.230)	(0.195)
Population	0.406**	0.159*	0.317***	0.389***	0.308***	0.342***	0.311***	0.312***	0.311***
	(0.200)	(0.097)	(0.089)	(0.081)	(0.049)	(0.037)	(0.067)	(0.065)	(0.058)
GDP per Capita	0.885	0.129	0.203	0.136	0.303***	0.307***	0.344	0.363	0.199
	(0.542)	(0.287)	(0.216)	(0.176)	(0.088)	(0.103)	(0.244)	(0.236)	(0.206)
Resource Rents	0.027	−0.062	−0.004	0.064	0.000	0.055	0.008	−0.009	−0.083
	(0.192)	(0.101)	(0.115)	(0.111)	(0.048)	(0.069)	(0.085)	(0.080)	(0.072)
DAC Aid	0.042	0.050	0.096**	0.038	0.124*	0.070	0.002	0.004	0.004
	(0.180)	(0.098)	(0.045)	(0.055)	(0.064)	(0.056)	(0.062)	(0.058)	(0.057)
Chinese Finance	−0.059	0.026	−0.005	0.004	−0.001	−0.019	−0.001	−0.005	−0.002
	(0.057)	(0.024)	(0.027)	(0.011)	(0.018)	(0.031)	(0.014)	(0.017)	(0.023)
IMF Program	0.317	−0.099	0.536	−0.033	0.020	−0.333**	0.435	0.447	0.354*
	(0.395)	(0.237)	(0.455)	(0.239)	(0.162)	(0.150)	(0.275)	(0.277)	(0.206)
UNSC Member	−1.217	−1.125***	0.420	−0.075	0.105	−0.358	0.558**	0.649***	0.520**
	(0.846)	(0.282)	(0.555)	(0.390)	(0.294)	(0.316)	(0.233)	(0.246)	(0.220)
Ideal Point Dist.	6.051*	3.382	−0.046	2.391	0.274	0.122	1.240	1.752	0.859
	(3.431)	(2.428)	(2.713)	(1.572)	(0.850)	(1.377)	(1.173)	(1.251)	(0.989)
Intercept	−29.145***	−15.159***	−18.158***	−16.394***	−18.069***	−17.949***	−17.271***	−18.313***	−16.614***
	(7.703)	(3.515)	(2.410)	(1.849)	(0.945)	(0.847)	(2.743)	(2.682)	(2.129)
Observations	9536	9536	9536	9536	9536	9536	9536	9536	9536
AIC	72.3	72.3	73.4	76.0	77.5	73.9	75.6	75.1	75.4
BIC	330.2	330.2	331.2	333.9	335.4	331.8	333.4	333.0	333.3

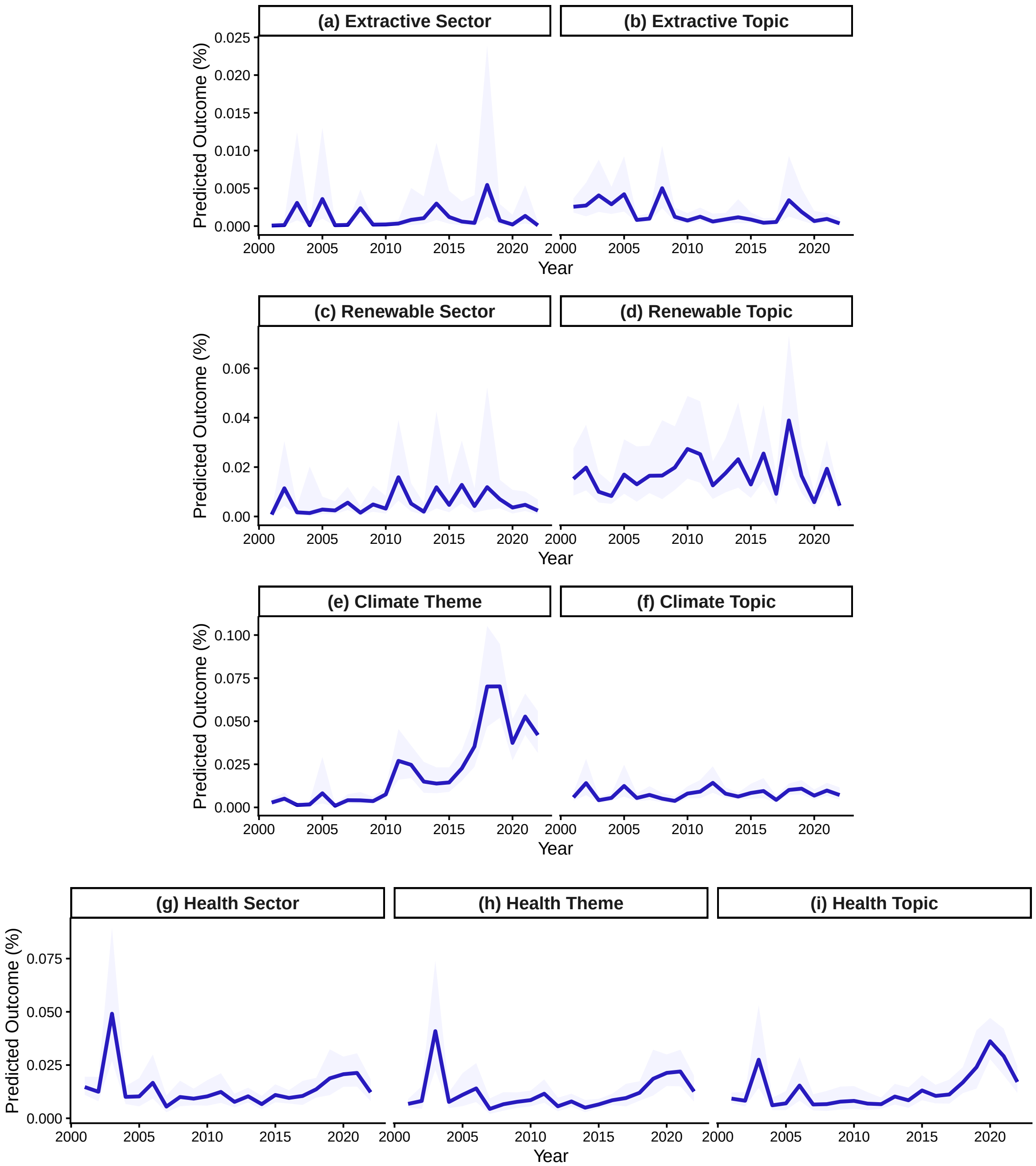
This table presents the results of nine fractional logistic regressions with standard errors clustered by country and year. All independent variables are lagged at $t-1$. The coefficients for year fixed effects are omitted from the table for brevity. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Figure H.2: Predicted Project Commitment (Log USD, Year Fixed Effects)



These panels display the average predicted new IDA and IBRD commitment (in logged 2023 USD) per project each year, as a function of a project's share of extractive, renewable, climate, and health content. These predictions are based on linear regressions reported in Table H.2, holding all numeric covariates at their means and categorical covariates at their reference categories. Note that each row has its own y-axis scale.

Figure H.3: Predicted Project Commitment (% of Total Commitments, Year Fixed Effects)



These panels display the average predicted new IDA and IBRD commitment (as a percentage of total new annual IDA and IBRD commitments) per project each year, as a function of a project's share of extractive, renewable, climate, and health content. These predictions are based on fractional logistic regressions reported in Table H.3, holding all numeric covariates at their means and categorical covariates at their reference categories. Note that each row has its own y-axis scale.

H.2 *After 2019* Dummy

As mentioned in the previous section, the main analysis uses splines to model a gradual evolution in the World Bank's project portfolio. Tables H.4 to H.6 replace the splines with an *After 2019* dummy (as the Bank pledged to cease oil and gas funding after 2019). Table H.4, for instance, identifies a significant *increase* in the climate theme share (Model e) and a significant *decrease* in the climate topic share (Model f) after 2019, a discrepancy that does not exist for any other area of interest.

Table H.4: Predictors of Project Sector, Theme, and Topic, 2001–2022 (With *After 2019* Dummy)

	(a) Extractive Sector Share	(b) Extractive Topic Share	(c) Renewable Sector Share	(d) Renewable Topic Share	(e) Climate Theme Share	(f) Climate Topic Share	(g) Health Sector Share	(h) Health Theme Share	(i) Health Topic Share
After 2019	−0.010***	−0.020***	−0.006***	−0.035***	0.168***	−0.017***	0.139***	0.156***	0.180***
	(0.002)	(0.003)	(0.002)	(0.007)	(0.027)	(0.005)	(0.015)	(0.014)	(0.017)
Governance	−0.005**	0.002	0.006	0.010	0.023**	0.036***	−0.022***	−0.026***	−0.040***
	(0.002)	(0.004)	(0.006)	(0.009)	(0.010)	(0.010)	(0.008)	(0.006)	(0.010)
Election Year	0.000	0.003	−0.003	0.003	−0.001	−0.012*	−0.006	−0.005	−0.006***
	(0.002)	(0.002)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.002)
EITI Member	0.007**	0.017***	−0.001	−0.015*	0.036*	0.006	−0.003	−0.001	0.000
	(0.003)	(0.005)	(0.005)	(0.007)	(0.019)	(0.009)	(0.005)	(0.005)	(0.008)
Field Discovery	0.002	0.005	−0.005	−0.011	0.011	0.011	−0.009	−0.011	−0.011
	(0.003)	(0.004)	(0.005)	(0.011)	(0.013)	(0.010)	(0.011)	(0.009)	(0.010)
SIDS	0.005	0.003	0.007	−0.001	0.086***	0.020	−0.021**	−0.021**	−0.024*
	(0.004)	(0.007)	(0.008)	(0.014)	(0.023)	(0.017)	(0.010)	(0.008)	(0.012)
Disaster	−0.001	0.007**	−0.005	−0.027***	0.002	0.018**	0.007	0.010	0.014
	(0.003)	(0.003)	(0.003)	(0.009)	(0.010)	(0.006)	(0.007)	(0.007)	(0.009)
Population	−0.001	−0.003**	0.002	0.009**	0.017***	0.005	−0.008**	−0.008***	−0.011***
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
GDP per Capita	0.003***	−0.001	−0.004	0.000	0.012	0.018***	−0.002	0.001	−0.008
	(0.001)	(0.002)	(0.002)	(0.006)	(0.008)	(0.006)	(0.005)	(0.004)	(0.005)
Resource Rents	0.002***	0.002*	−0.001	0.000	−0.007*	0.004	0.003	0.002	−0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
DAC Aid	0.001	0.001	0.002	−0.001	−0.001	−0.003	−0.002	−0.002	−0.004
	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)
Chinese Finance	0.000	0.000	0.000	−0.001	0.000	−0.001	0.001	0.001**	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
IMF Program	0.003	0.001	−0.002	−0.008	−0.036***	−0.014**	−0.003	−0.006	0.001
	(0.002)	(0.003)	(0.004)	(0.005)	(0.010)	(0.007)	(0.005)	(0.004)	(0.007)
UNSC Member	0.003	−0.008***	−0.002	−0.016*	−0.011	−0.004	0.009	0.009	0.002
	(0.003)	(0.002)	(0.005)	(0.008)	(0.014)	(0.011)	(0.008)	(0.005)	(0.009)
Ideal Point Dist.	0.003	−0.017	0.010	0.069	0.169*	−0.049	−0.067**	−0.058***	−0.087**
	(0.016)	(0.018)	(0.023)	(0.043)	(0.091)	(0.050)	(0.025)	(0.020)	(0.040)
Intercept	−0.005	0.074**	0.035	−0.051	−0.271**	−0.105	0.221***	0.172***	0.300***
	(0.019)	(0.027)	(0.023)	(0.070)	(0.105)	(0.072)	(0.060)	(0.052)	(0.060)
Observations	9536	9536	9536	9536	9536	9536	9536	9536	9536
AIC	−21 868.9	−15 781.2	−10 788.3	−1655.8	1781.6	−768.3	625.6	−1153.7	632.6
BIC	−21 754.3	−15 666.6	−10 673.7	−1541.2	1896.2	−653.7	740.3	−1039.1	747.2

This table presents the results of nine fractional logistic regressions with standard errors clustered by country and year. All independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table H.5: Predictors of Project Commitment (Log USD), 2001–2022 (With *After 2019* Dummy)

	(a) Extractive Sector Log USD	(b) Extractive Topic Log USD	(c) Renewable Sector Log USD	(d) Renewable Topic Log USD	(e) Climate Theme Log USD	(f) Climate Topic Log USD	(g) Health Sector Log USD	(h) Health Theme Log USD	(i) Health Topic Log USD
After 2019	−0.211***	0.295	0.078	0.203	8.787***	0.396**	2.454***	2.833***	2.506***
	(0.032)	(0.202)	(0.069)	(0.249)	(1.133)	(0.168)	(0.260)	(0.265)	(0.317)
Governance	−0.113	0.017	0.149	0.188	0.661**	0.478***	−0.087	−0.213	−0.367**
	(0.075)	(0.111)	(0.139)	(0.140)	(0.277)	(0.113)	(0.218)	(0.185)	(0.142)
Election Year	0.017	0.022	−0.060	0.063	0.059	−0.168*	−0.064	−0.079	0.044
	(0.056)	(0.057)	(0.066)	(0.069)	(0.248)	(0.091)	(0.158)	(0.129)	(0.081)
EITI Member	0.267***	0.269**	−0.094	−0.252	1.874**	0.004	−0.407*	−0.347*	−0.027
	(0.091)	(0.102)	(0.139)	(0.151)	(0.799)	(0.141)	(0.199)	(0.168)	(0.123)
Field Discovery	0.144	0.063	−0.054	−0.131	−0.127	0.162	−0.165	−0.312	−0.142
	(0.106)	(0.112)	(0.144)	(0.148)	(0.401)	(0.129)	(0.260)	(0.224)	(0.152)
SIDS	0.043	0.015	0.053	−0.157	1.825***	0.243	−0.586**	−0.585**	−0.428**
	(0.078)	(0.181)	(0.214)	(0.142)	(0.564)	(0.250)	(0.272)	(0.261)	(0.200)
Disaster	0.035	0.016	−0.227**	−0.369**	−0.275	0.023	0.279	0.265	0.057
	(0.089)	(0.100)	(0.089)	(0.149)	(0.256)	(0.106)	(0.175)	(0.195)	(0.133)
Population	−0.041**	0.270***	0.062	0.428***	0.527***	0.419***	−0.199***	−0.146***	0.188***
	(0.018)	(0.036)	(0.043)	(0.047)	(0.093)	(0.038)	(0.064)	(0.048)	(0.046)
GDP per Capita	0.052	0.005	−0.165**	0.042	0.205	0.250***	−0.206	−0.118	−0.075
	(0.036)	(0.059)	(0.059)	(0.084)	(0.230)	(0.088)	(0.134)	(0.117)	(0.083)
Resource Rents	0.038***	−0.018	0.009	−0.024	−0.207	0.019	0.081	0.033	−0.069
	(0.011)	(0.032)	(0.032)	(0.034)	(0.133)	(0.041)	(0.053)	(0.049)	(0.044)
DAC Aid	0.014	0.054	0.009	0.038	0.003	0.002	−0.075	−0.089*	0.009
	(0.011)	(0.063)	(0.039)	(0.042)	(0.135)	(0.039)	(0.047)	(0.051)	(0.048)
Chinese Finance	0.001	0.016	−0.005	0.003	0.017	−0.004	0.025	0.029*	0.025
	(0.005)	(0.014)	(0.007)	(0.013)	(0.058)	(0.012)	(0.018)	(0.015)	(0.019)
IMF Program	0.087	0.053	−0.119	−0.066	−0.873***	−0.131	0.171	0.214*	0.051
	(0.053)	(0.083)	(0.082)	(0.095)	(0.295)	(0.111)	(0.136)	(0.110)	(0.114)
UNSC Member	0.035	−0.150	0.006	−0.275**	−0.757	−0.043	0.342	0.407**	0.011
	(0.102)	(0.130)	(0.164)	(0.114)	(0.451)	(0.141)	(0.208)	(0.153)	(0.157)
Ideal Point Dist.	−0.215	1.533**	0.366	2.329***	5.705*	1.363*	−2.169**	−1.644*	1.172
	(0.296)	(0.686)	(0.727)	(0.694)	(3.240)	(0.772)	(0.829)	(0.847)	(0.764)
Intercept	0.362	4.412***	1.218*	2.543**	−7.091**	1.249	7.301***	5.274***	6.862***
	(0.464)	(0.892)	(0.630)	(1.098)	(2.520)	(0.805)	(1.520)	(1.328)	(1.085)
Observations	9536	9536	9536	9536	9536	9536	9536	9536	9536
R^2	0.007	0.057	0.002	0.058	0.234	0.082	0.024	0.033	0.085

This table presents the results of nine linear regressions with standard errors clustered by country and year. All independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table H.6: Predictors of Project Commitment (Share of Total Commitments), 2001–2022 (With *After 2019* Dummy)

	(a) Extractive Sector Share Commit.	(b) Extractive Topic Share Commit.	(c) Renewable Sector Share Commit.	(d) Renewable Topic Share Commit.	(e) Climate Theme Share Commit.	(f) Climate Topic Share Commit.	(g) Health Sector Share Commit.	(h) Health Theme Share Commit.	(i) Health Topic Share Commit.
After 2019	−0.990	−0.816**	−0.548***	−0.677*	0.679***	−0.045	0.422***	0.644***	0.937***
	(0.986)	(0.339)	(0.164)	(0.411)	(0.260)	(0.094)	(0.154)	(0.168)	(0.185)
Governance	−1.572*	−0.468	0.339	0.162	−0.097	0.666***	−0.257	−0.352*	−0.595**
	(0.844)	(0.409)	(0.275)	(0.295)	(0.143)	(0.250)	(0.207)	(0.203)	(0.245)
Election Year	−0.512	−0.366	−0.458	0.282	0.031	0.113	0.083	0.028	−0.032
	(0.543)	(0.288)	(0.297)	(0.200)	(0.125)	(0.207)	(0.082)	(0.099)	(0.112)
EITI Member	−0.390	−0.206	−0.568*	−0.328*	0.568***	0.261**	0.122	0.169	0.263
	(0.526)	(0.229)	(0.338)	(0.182)	(0.194)	(0.129)	(0.209)	(0.203)	(0.178)
Field Discovery	−1.158	0.546	−0.155	−0.550*	−0.112	−0.195	−0.491	−0.566	−0.535*
	(1.015)	(0.468)	(0.455)	(0.315)	(0.187)	(0.199)	(0.323)	(0.365)	(0.282)
SIDS	−1.364**	−0.594	−0.854	−0.876**	−0.111	−0.037	−0.626***	−0.818***	−0.661***
	(0.632)	(0.454)	(0.618)	(0.413)	(0.179)	(0.202)	(0.231)	(0.192)	(0.176)
Disaster	−0.292	0.211	−0.527*	−0.429	−0.067	0.333	0.233	0.229	0.198
	(1.180)	(0.359)	(0.315)	(0.302)	(0.199)	(0.211)	(0.205)	(0.202)	(0.189)
Population	0.397**	0.134	0.345***	0.383***	0.377***	0.362***	0.300***	0.302***	0.305***
	(0.171)	(0.095)	(0.072)	(0.068)	(0.027)	(0.026)	(0.061)	(0.058)	(0.054)
GDP per Capita	1.009	0.160	0.181	0.143	0.276***	0.320***	0.321	0.351*	0.189
	(0.628)	(0.314)	(0.183)	(0.160)	(0.075)	(0.091)	(0.217)	(0.202)	(0.187)
Resource Rents	−0.043	−0.060	−0.041	0.032	−0.110**	0.057	−0.021	−0.047	−0.123**
	(0.176)	(0.103)	(0.099)	(0.097)	(0.051)	(0.071)	(0.076)	(0.069)	(0.063)
DAC Aid	−0.008	0.013	0.084**	0.039	0.079**	0.058	−0.004	0.000	0.004
	(0.122)	(0.085)	(0.036)	(0.044)	(0.038)	(0.046)	(0.059)	(0.051)	(0.053)
Chinese Finance	−0.058	0.004	0.013	0.012*	0.009	−0.016	−0.003	−0.003	0.002
	(0.038)	(0.015)	(0.017)	(0.007)	(0.010)	(0.019)	(0.012)	(0.013)	(0.013)
IMF Program	0.267	0.054	0.426	−0.095	−0.187	−0.345***	0.519*	0.513*	0.345*
	(0.308)	(0.223)	(0.442)	(0.206)	(0.166)	(0.123)	(0.296)	(0.299)	(0.197)
UNSC Member	−1.362	−1.132***	0.308	−0.111	0.015	−0.259	0.513***	0.590***	0.432**
	(1.019)	(0.302)	(0.489)	(0.365)	(0.199)	(0.318)	(0.169)	(0.179)	(0.172)
Ideal Point Dist.	4.605	1.851	0.788	1.663	2.361**	0.808	0.906	1.141	0.802
	(2.851)	(2.678)	(2.168)	(1.334)	(1.009)	(1.386)	(1.063)	(1.168)	(0.892)
Intercept	−26.821***	−15.089***	−16.446***	−15.989***	−17.495***	−18.211***	−17.028***	−17.543***	−16.257***
	(7.635)	(3.508)	(1.943)	(1.697)	(0.845)	(0.924)	(2.347)	(2.241)	(1.848)
Observations	9536	9536	9536	9536	9536	9536	9536	9536	9536
AIC	32.3	32.3	33.4	36.0	37.5	33.9	35.6	35.1	35.4
BIC	146.9	146.9	148.0	150.6	152.1	148.5	150.2	149.7	150.0

This table presents the results of nine fractional logistic regressions with standard errors clustered by country and year. All independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$