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

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Abstract

How do international organizations balance contradictory goals, like addressing climate change while promoting economic growth? In recent years, the World Bank has pledged to support climate-friendly development and reduce funding for fossil fuel projects. Yet high-profile instances of continued support for oil and gas projects — in Guyana, Indonesia, and elsewhere — have cast doubt on this pledge. This study uses text analysis and statistics to examine all World Bank projects approved between 2001 and 2022. We find show that the World Bank became significantly less likely to fund extractive projects and more likely to fund climate projects after 2019. Each climate project attracted more finance in absolute terms, but not relative to the Bank's expanding overall budget, whereas finance per extractive project remained stable. These findings reveal a complex balancing act: while the Bank has embraced climate priorities, it continues to invest in extractive industries.

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1 Introduction

How do international organizations balance competing missions and demands from principals? In response to calls for more emphasis on sustainable development, the World Bank Group released its first Climate Change Action Plan in 2016. Recognizing that climate change posed a threat to its core mission of ending poverty and boosting prosperity, the Bank promised to increase climate finance from 21 to 28 percent of its total budget by 2020. A second Climate Change Action Plan, released in 2020, set a more ambitious target of 35 percent, with a focus on adaptation. In parallel, during the 2017 One Planet Summit, the World Bank Group announced that it would no longer finance upstream oil and gas projects by 2019.[1] In 2021, its two private sector institutions — the International Finance Corporation (IFC) and the Multilateral Investment Guarantee Agency (MIGA) — vowed to stop indirectly supporting new coal-fired power projects. All this reflects the Bank's stated desire to align 100 percent of its operations with the objectives of the Paris Agreement by 2025, providing support "consistent with low-carbon and climate-resilient development pathways" to help countries reach their Nationally Determined Contributions and Long-Term Strategies (World Bank Group, 2021, 15).

The widespread consensus is that the Bank upheld its first promise: by COP28 in 2023, it had surpassed the 35 percent goal and was aiming for 45 percent of climate finance — about 40 billion dollars — in the following fiscal year.[2] As of 2023, it is the single largest provider of multilateral climate finance to low- and middle-income countries (European Investment Bank, 2024). There is less consensus about the second promise, with environmental groups accusing the Bank of deception. In 2020, Guyana received $55 million to train oil and gas officials and revamp the banking and insurance sectors to support the fossil fuel industry.[3] In

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

[2] World Bank Group. 2023. *Press Release: World Bank Group Doubles Down on Financial Ambition to Drive Climate Action and Build Resilience.*

[3] Jasper Jolly. 2020. "Anger Over World Bank's $55M Pledge to Guyana's Fossil Fuel Industry." *The Guardian.*

2023, the IFC indirectly backed the construction of two Indonesian coal-fired power plants.[4] Yet these financing decisions do not involve *upstream* oil and gas projects or *new* coal-fired power plants.[5] Rather, they fall under an exception the World Bank had made in its original 2017 announcement: "in exceptional circumstances" and "in the poorest countries," it 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."[6] This reflects the complicated mission of international organizations (IOs), which must please multiple constituents by pursuing potentially conflicting goals, like decarbonization and development. As a result, IOs might embrace commitments that are lofty and ambitious, but also soft and flexible.

Are Guyana and Indonesia "exceptional circumstances?" To what extent has the World Bank increased climate finance and reduced oil and gas finance, especially after 2019? We answer this using 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.[7] Recognizing that the Bank faces incentives to overstate the amount of climate financing it provides, we first use keyword-assisted topic models (Eshima, Imai and Sasaki, 2024) to describe each project's content and validate the official project classification. A subsequent statistical analysis shows that the Bank became significantly less likely to fund extractive projects and more likely to fund climate-related projects after 2019. However, these shifts reflect the continuation of a decade-long trend, not an abrupt change in funding priorities. After 2019, each climate-related project has attracted more finance in absolute terms, but not as a share of the total lending portfolio. Meanwhile,

[4] David Stanway and Fransiska Nangoy. 2023. "Green Groups Slam World Bank for Backing Indonesian Coal Plants." *Reuters*.

[5] Indonesia's Suralaya plant already had eight units in operation.

[6] 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.*

[7] Ideally, IDA and IBRD data would be paired with IFC and MIGA data to see if the latter two eliminated support for new coal-fired power projects after 2021. Unfortunately, IFC and MIGA work with private actors and do not publish their data.

the financial scale of each extractive project has remained constant, though such projects are now significantly more likely to end. Overall, the Bank seems to be taking incremental steps to align its operations with the objectives of the Paris Agreement while sustaining fossil fuel projects it considers necessary.

As the two Bretton Woods institutions, the International Monetary Fund (IMF) and the World Bank have overlapping tasks (Marchesi and Sirtori, 2011), yet researchers know much more about the former than the latter. Countries borrow from the IMF because they need emergency funding to prevent economic collapse, of course, but also because they want to use the IMF as a scapegoat to justify unpopular economic reforms (Vreeland, 2003; Moser and Sturm, 2011). Like the World Bank, the IMF conditions loan disbursement to a series of policy reforms that catalyze private borrowing (Chapman et al., 2017), foreign direct investment (Woo, 2013), and natural resource governance (Goes, 2023), but also reduce spending on education (Stubbs et al., 2020) and public sector wages (Rickard and Caraway, 2019), increase income inequality (Forster et al., 2019; Lang, 2021), and even magnify the risk of a coup (Casper, 2017). The IMF's narrow focus on fiscal consolidation often comes at the expense of the environment, as loans are associated with a significant increase in deforestation (Forster, Bhandary and Gallagher, 2024). US preferences significantly influence the scope of IMF conditions, though local circumstances also matter (Stone, 2008; Dreher, Sturm and Vreeland, 2015, 2009*b*). And over two-thirds of all IMF loans between 1980 and 2015 were interrupted due to non-compliance with conditions (Reinsberg, Stubbs and Kentikelenis, 2022).

Until recently, researchers knew comparatively little about World Bank lending, at least in quantitative terms, due to data limitations (but see Winters, 2010; Hernandez, 2017; Malik and Stone, 2018; Clark and Dolan, 2021; Cormier and Manger, 2022). Now that project-level information is available, it is important to look at the World Bank as a standalone actor because its role in the global economy is entirely different: it is not a crisis lender, like the IMF, but a long-term development lender that rarely cancels its loans, even when borrowers fail to comply with conditions (Dreher, 2004). While not immune to political interference (Kersting and Kilby, 2016; Kilby, 2009), the World Bank is less reliant on the financial contributions of its member countries, as it can cover its entire operating budget by borrowing from financial markets (Nielson and Tierney, 2003). As a result, the Bank has more budgetary autonomy and tends to stipulate less pervasive — if more numerous — conditions than the IMF (Dreher, 2004). This means the Bank might have more discretion to provide climate finance, but also less leverage to push for climate policy, as it is unlikely to punish borrowers for non-compliance.

Our main contribution is to connect multilateral lending to climate politics and extractive industries, explaining how IOs have competing interests in these sectors. 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 are mixed: they reflect the Bank's need to balance competing missions, pleasing principals with disparate and often rapidly changing interests.

2 Climate Policy and Multilateral Lending

Multilateral lending is a political affair. In the World Bank and IMF alike, loan approval falls under the purview of the respective Executive Boards, which are largely controlled by the US. Important US trade partners or bilateral aid recipients tend to receive larger World Bank loans (Fleck and Kilby, 2006), whereas temporary members of the UN Security Council attract more frequent funding from both institutions (Dreher, Sturm and Vreeland, 2009*a*,*b*) and receive IMF loans with fewer conditions (Dreher, Sturm and Vreeland, 2015). When countries' voting behavior in the UN General Assembly aligns with that of the US, the Bank tends to disburse loans faster, especially ahead of competitive executive elections (Kersting and Kilby, 2016). While World Bank lending is ostensibly client-oriented and needs-based (Cormier, 2016), prioritizing well-governed borrowers (Winters, 2010), macroeconomic performance is a secondary consideration when lending to US allies (Kilby, 2009). The World Bank makes fewer demands when its borrowers simultaneously receive aid from new donors like China, India, Saudi Arabia, and the United Arab Emirates (Hernandez, 2017). Its staff tends to design programs compatible with US preferences (Clark and Dolan, 2021) — and US preferences regarding climate policy can vary considerably from one administration to another. In fact, a considerable chunk of multilateral climate finance comes from multi-donor trust funds, made up of voluntary contributions that are kept separate from IO's primary budgets (Arias and Clark, 2024). In earmarking their voluntary contributions, donors like the US 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 — at least in the case of the World Bank (Reinsberg 2017; see also Eichenauer and Reinsberg 2017).

The most powerful members of the Bretton Woods institutions are responsible for the most carbon emissions. Those least responsible for such emissions and most vulnerable to climate change have the least decision-making power. 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.[8] The 68 developing countries that self-identify as climate-vulnerable (V20) are responsible for 5 percent of global emissions and — as of 2024 — command an IMF vote share of just 6.7 percent, with similar figures for the World Bank (Merling and Forster, 2024, 552).

Even as the World Bank claims to have "a significant track record of advancing climate action" (World Bank Group, 2021, 5), promising to increase climate funding and mobilize additional private capital, skeptics point to the institution's so-called organized hypocrisy: its

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

rhetoric changes much faster than its reality (Weaver, 2008). This hypocrisy reflects not only the need for World Bank bureaucrats to please multiple political masters with heterogeneous and inconsistent preferences but also IO's pathologies and dysfunctions more broadly. If the World Bank is so beholden to the wants of its important principals, selectively pursuing its mandate, only weakly complying with rules, and only half-heartedly attempting to implement new agendas (Weaver, 2008, 21), why should it seriously pursue the most ambitious and expensive of all agendas — climate change mitigation? Given the pressure to compete against new donors with notoriously unambitious climate policies, like China (Tørstad, Sælen and Bøyum, 2020), why should the World Bank refrain from funding oil, gas, and coal projects that might get funded anyway — and by a US rival to boot? Indeed, Zeitz (2021) shows that competition can drive the World Bank to emulate China by funding projects in infrastructure-intensive sectors (including oil and gas) and possibly relaxing environmental safeguard requirements.

Still, IOs are independent actors with their own agendas (Barnett and Finnemore, 1999). In particular, the World Bank has remarkable financial autonomy, raising enough money in capital markets to cover all of its operating budget (Nielson and Tierney, 2003). IMF staff care about the climate (Clark and Zucker, 2023), to the point of extending 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).

In addition, IO staff care about their employer's reputation. Non-governmental organizations can meaningfully influence 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. Cormier and Manger (2022) show that shifts in the World Bank's research program affect the content of loan conditionality; for instance, as staff research increasingly covers domestic ownership, more and more loan conditions reflect this concern. And even after the Executive Board approves investment project loans (tied to specific projects), World Bank staff with country experience and good supervisory ability play a key role in recipient performance (Heinzel and Liese, 2021).

In sum, World Bank staff care about the environment, want to uphold their reputation, have relative discretion over how to distribute loans, and directly influence loan implementation. Therefore, we should expect World Bank loans to take climate issues seriously.

At the leadership level, G-7 countries have become more environmentally concerned, pushing for reforms in 1993–1994 that increased 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). The World Bank's most important principals might not be willing to reduce their own emissions, but 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. Ultimately, even "weak" states can wield outsize influence in international climate negotiations, since their climate vulnerability legitimizes their salient positions (Genovese, 2020).

If there is an increase in environmental concerns among both leadership and rank-and-file staff, as previous research implies, there might be a corresponding increase in funding for, say, renewable energies and coastal zone management. World Bank leadership may support mitigation finance more 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). Either way, there should be a gradual increase in aggregate climate finance. In parallel, the World Bank's 2017 announcement should be more than cheap talk: after 2019, there should be an abrupt halt in financing for upstream oil and gas projects.

3 Extractive Industries and Multilateral Lending

In financial terms, extractive industries far exceed multilateral lending. In 2023, the World Bank Executive Board approved 322 projects worth a modest \$72.8 *billion*, whereas mineral fuel and oil exports totaled \$1.89 *trillion*.[9] There is no shortage of ways natural resources can hurt institutional quality: they are 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). While the direct effect of natural resources on long-run growth is positive, the indirect effect through price volatility is negative, reflecting the fact that oil, gas, and mineral prices are all but impossible to forecast (van der Ploeg and Poelhekke, 2009). Finally, resource wealth tends to hinder economic diversification by crowding out investment in other sectors of the economy and prompting a currency appreciation that makes non-resource exports less competitive on the global market.

But if, against all odds, resource-rich countries overcome these challenges, well-managed resource revenues can fund development projects, improve infrastructure, and reduce poverty (Venables, 2016). While windfalls cannot *replace* multilateral lending (which comes with technical assistance and policy expertise no amount of oil or gas money can buy), they can fill important financing gaps, in addition to increasing the odds of loan repayment and reducing the need for additional loans (Goes and Kaplan, 2024). Repayment concerns might be most pressing for the world's lender of last resort, which tends to give larger loans to countries in the worst financial standing. Indeed, IMF loans with resource-rich countries pay close attention to the extractive sector, as does IMF surveillance (Goes, 2023; Goes and Chapman, 2024). But the IMF is not alone: this is one of the few sectors where all major IOs — the IMF, World Bank, UN, European Union, African Union, G8, G20, and others

[9]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."

— provide consistent recommendations (Sovacool et al., 2016; David-Barrett and Okamura, 2016). The key recommendation is to join the Extractive Industries Transparency Initiative (EITI), established in 2002–2003. EITI adherence was initially an unspoken requirement to reach Heavily Indebted Poor Country (HIPC) status, which would make countries eligible for special assistance from the World Bank and the IMF (David-Barrett and Okamura, 2016). Put simply, transparency in the extractive sector is so important to the international community that Bretton Woods institutions informally conditioned loan disbursement to such reforms, at least for a while.

Through a three-stage implementation process (commitment, candidacy, and compliance), EITI adherents are expected to disclose their payments and revenues, promote local economic development and diversification, foster gender equality in the extractive sector, and make oil and gas markets more competitive, all while reducing the environmental impact of extractive activities. To be fair, evidence of EITI's effectiveness is mixed. It has not meaningfully 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). Self-selection plays a role, as more corrupt countries are less likely to join the initiative (David-Barrett and Okamura, 2016). Still, there are notable positive downstream effects. In boosting government revenues and improving environmental policies, EITI can reduce deforestation (Kinda and Thiombiano, 2024). In promoting data dissemination and stakeholder dialogue, EITI can increase trust in politicians (Fenton Villar, 2020). Even if this initiative is not a panacea, there are plenty of reasons why IOs might continue to support it.

Numerous World Bank projects since 2005, from Albania to Zambia, have funded EITI implementation and related initiatives to promote good governance within the extractive sector.[10] The choice to continuously support these projects, rather than advise borrowers to

[10] In addition to funding EITI implementation directly, the World Bank houses two multi-donor trust funds, the Extractive Industries Transparency Initiative (2004–2016) and the Extractives Global Programmatic Support (2015–2026), that pool resources from various sovereign development agencies to support EITI. See Reinsberg (2017) for more information about trust funds.

abandon their extractive industries altogether, might be rooted in pragmatism. 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 to the extractive sector. In addition, withdrawing funding or conditioning it to environmental reforms is unlikely to deter resource-rich countries from prospecting; should the World Bank's environmental demands prove too onerous, recipients can choose Chinese financing instead (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 with transparency. Given these priorities, it is unsurprising that the 2017 announcement to stop upstream oil and gas funding made exceptions for transparency initiatives in the energy sector.

Relatedly, the World Bank might continue to fund oil and gas projects if it considers that the developmental benefits outweigh the climate costs. For instance, in choosing to provide a grant to train Guyanese oil and gas sectors, as it did in 2020, the Bank likely considered Guyana's minimal carbon footprint. As of 2024, 93 percent of Guyana is covered in forest, and it produces less than one percent of the world's oil. Yet half of its 800,000 citizens live below the poverty line, and oil revenues can make a difference. Since oil production began, the Guyanese economy already grew a staggering 43.48 percent in 2020, 20.06 percent in 2021, and 63.37 percent in 2022.[11] In light of these projections, concerns about a poorly-managed natural resource sector might supersede climate concerns.

Besides, recipients are increasingly critical of the notion that they should scale back on resource production when donors are unwilling to do the same. If anything, Canada, Norway, the US, and others have increased hydrocarbon production in recent years, undermining the World Bank's stated commitment to stop funding upstream oil and gas projects.[12] As an illustration, Guyana's president Irfaan Ali declared in 2023: "53% of the world energy mix

[11] World Development Indicators 2024.

[12] 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 U.S. Oil Production Brings Down Prices and Raises Climate Fears." *The New York Times*.

comes from oil and gas. Even if we end up in a situation in 2070 and beyond — where, let's say, 40% of the energy mix comes from oil and gas — who determines who produces that 40%? These are questions that must be answered, because you can't just decide, You are out, you are in.' That is colonization in a different way."[13] Elsewhere, public officials echo these thoughts — like Ana Toni, Brazil's National Secretary for Climate Change, in 2024: "I wish countries richer than ours would have a real conversation about taking such steps, and not leave it to us vulnerable ones."[14] As these statements suggest, recipients would likely perceive a cut to oil and gas financing as hypocritical. IOs already face a legitimacy crisis as is. Across 121 countries, high-level civil servants perceive the World Bank and the IMF as biased and ineffective (Heinzel et al., 2020). Beyond eroding IO authority (Weaver, 2008), these perceptions can reduce compliance with conditionality and policy advice. Ultimately, the World Bank might not be in a position to make stringent demands, given that compliance with loan conditionality is low as is (Dreher, 2004). With these legitimacy concerns in mind, the World Bank may continue to support hydrocarbon projects after 2019, particularly in contexts where its authority is diminished.

In sum, even taking the Executive Board at its word and assuming the World Bank is sincerely committed to addressing climate change, there are multiple reasons why the organization might continue to finance extractive projects. Anticipating competition from China, India, Saudi Arabia, and others, the Bank might either fund upstream oil and gas projects on its own or provide a separate transparency component to projects already funded by new donors. The Bank may also consider that such projects bring more benefits than costs, at least "in exceptional circumstances" and "in the poorest countries." And it might conclude that withholding extractive funding would undermine its legitimacy, as recipients would view this decision as yet another evidence of IO hypocrisy. If any of these mechanisms is true, then there should be no sudden decline in oil and gas financing after 2019 — or,

[13] Gideon Long. 2023. "Guyana Scrambles to Make the Most of Oil Wealth." *BBC.*

[14] Max Bearak. 2024. "Brazil's Clashing Goals: Protect the Amazon and Pump Lots More Oil." *The New York Times.*

at most, a halt in financing for *upstream* oil and gas projects, but no decline for projects promoting good governance in the extractive sector.

4 Classifying World Bank Projects

4.1 Project Data

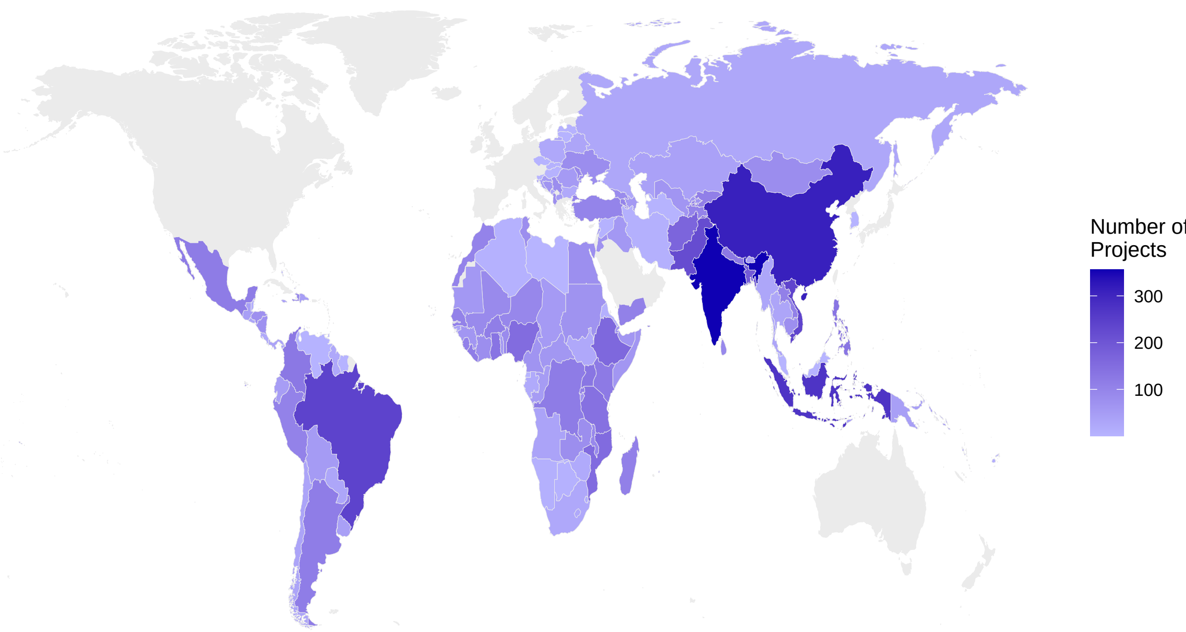
We use data on all projects approved by the World Bank Executive Board from January 2001 to December 2022, excluding projects that cannot be attributed to one single sovereign state or were dropped before securing Executive Board approval.[15] Figure 1 shows the geographic distribution of these projects.

While some of the projects are grants, most fall under one of three lending instruments that the World Bank offers to governments (Heinzel and Liese, 2021). Investment Project Financing (IPF) has a narrow focus: the Bank commits money to a particular infrastructure project that will 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.[16] To increase borrower 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 respectively for 63, 14, and 6 percent of all climate finance provided in 2023 (European Investment Bank, 2024).

[15] World Bank project information is available since May 1947, but the independent variables (discussed in Section 5.2) are not, hence the restricted time frame. In terms of dropped projects, those deemed financially unfeasible might be dropped at the concept review stage, whereas others failing to meet the Bank's environmental and social requirements might be dropped at the appraisal stage. Only 17 projects were dropped *after* securing Executive Board approval; these are included in the analysis.

[16] 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 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.

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



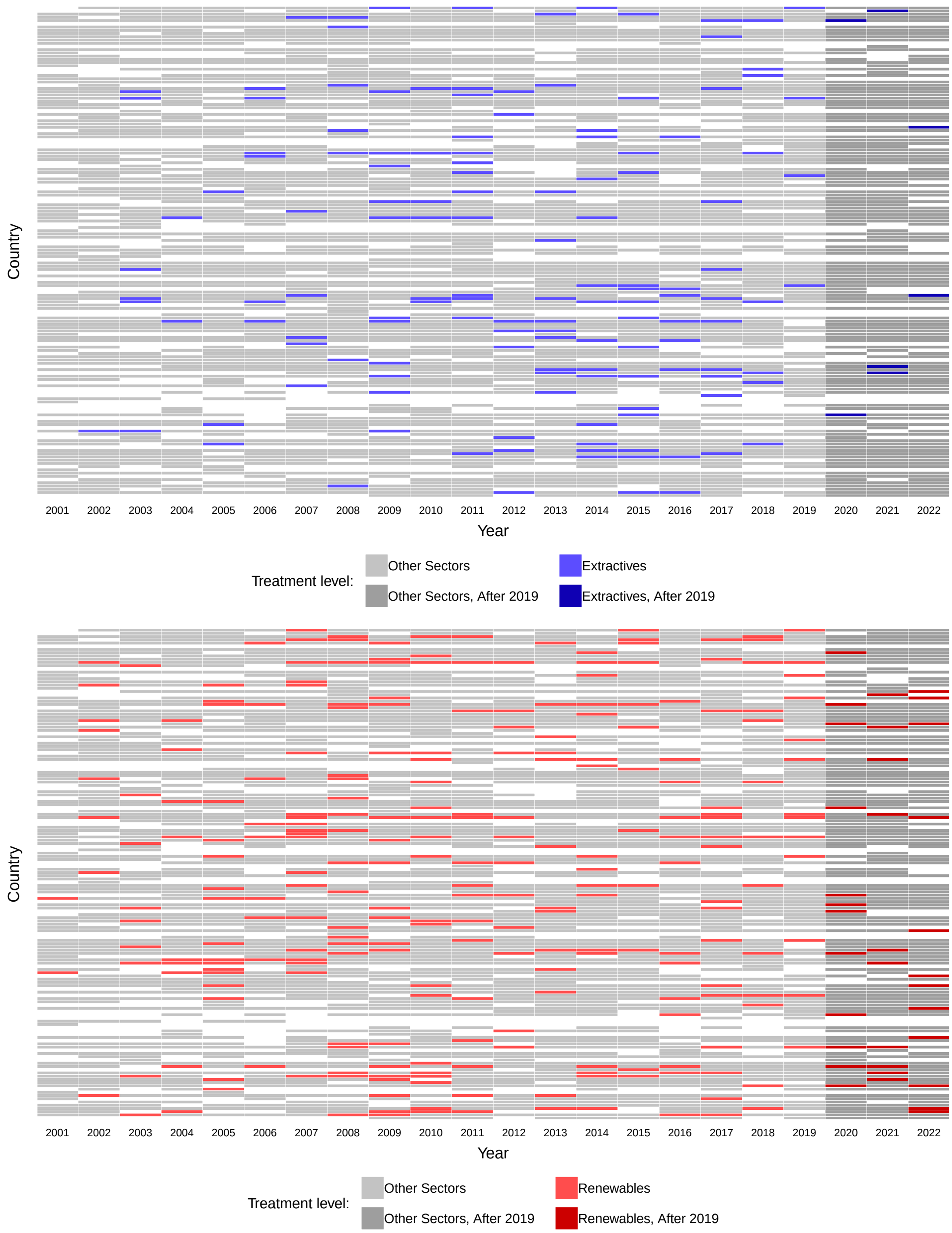
This map shows the number of projects approved by the World Bank Executive Board, distributed across 150 countries, between 2001 and 2022. This excludes projects that cannot be attributed to one sovereign state or were dropped before securing Executive Board approval. Countries in gray did not receive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

4.2 Project Taxonomies

The World Bank has two official project taxonomies. The most established taxonomy consists of 11 project *sectors*[17] that are not mutually exclusive and range from *Agriculture* (with subsectors like "crops," "irrigation," "forestry," and "livestock") to *Water/Sanitation/Waste* (with subsectors like "waste management" and "water supply"). We focus on seven subsectors under the broader *Energy and Extractives* sector. Specifically, we generate the dichotomous variable *Sector: Extractives*, which takes the value of one for all projects whose main subsector is "mining" or "oil and gas;" and the dichotomous variable *Sector: Renewables*, which takes the value of one for all projects whose main subsector is "renewable energy — biomass," "renewable energy — geothermal," "renewable energy — hydro," "renewable en-

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

Figure 2: World Bank Projects, by Sector, 2001–2022



This figure shows the distribution of World Bank projects across years (x-axis) and countries (y-axis, with labels removed for ease of visualization), highlighting projects whose main sector is extractive (top) or renewable (bottom). White cells indicate that the country in question did not receive any projects that year.

ergy — solar," or "renewable energy — wind."[18] Figure 2 shows the distribution of *Sector: Extractives* (top) and *Sector: Renewables* (bottom) across years and countries. As this figure shows, extractive projects — which were already fairly sparse until 2019 — became even less common after 2019, with only seven country-years recording funding in this sector.

This taxonomy has clear shortcomings: it is not exhaustive, and climate change is not a separate sector. Recognizing these limitations, the Bank introduced a new taxonomy in July 2016 consisting of eight overlapping project *themes*, including an *Environment and Natural Resource Management* theme and a "climate change" sub-theme. When the Bank talks about increasing climate finance to 45 percent of its total budget, it is using this updated taxonomy. According to the Bank's website, "this new taxonomy reflects corporate goals and priorities"[19] — but it also has three shortcomings. First, though pre-July 2016 data were retrofitted to this new taxonomy, the Bank warns that the two periods 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)."

Second, there is no theme for oil, gas, extractive industries, or non-renewable natural resources. Projects related to these topics often have a missing theme or are listed under *Other Public Sector Governance*, *Other Accountability/Anti-Corruption*, and *Other Environment and Natural Resources Management*. This raises transparency concerns: rather than phase out upstream oil and gas investments, the World Bank could simply have stopped classifying projects as such, obscuring the true nature of its investment portfolio. 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 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"

[18] 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.

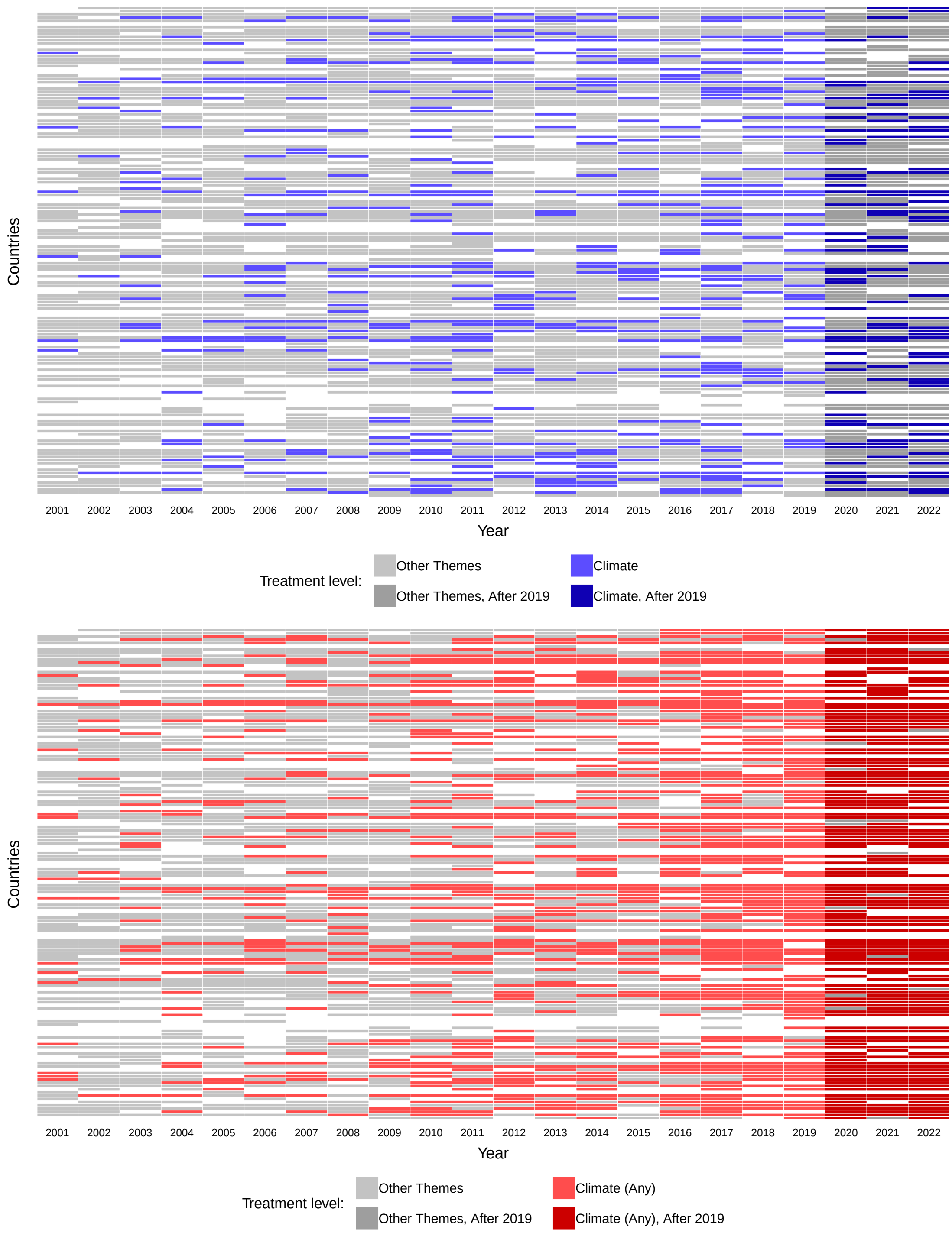
[19] https://projects.worldbank.org/en/projects-operations/project-theme

refers to energy efficiency, access, policies, and reform, without specifying the energy source.

Third, the new classification could be overstating the amount of climate funding by attributing the "climate" label to projects that are only indirectly related to this theme. Since projects can be assigned to multiple themes and sub-themes, the main theme likely reflects the project's core focus, with secondary themes reflecting broader institutional priorities. For example, three projects aiming to "improve market access of milk producers" (India, 2012), "provide relief to micro, small, and medium-size enterprises" (Georgia, 2021), or "mitigate the impact of the war in Ukraine on refugees and households" (Moldova, 2022) include a secondary climate label. These projects may be tangentially related to climate adaptation and mitigation, but calling them "climate funding" is arguably an embellishment. To illustrate this point, Figure 3 shows the number of countries and years with projects listing "climate change" as the *main* sub-theme (top panel) or as *any* sub-theme — main or secondary (bottom panel). While 80 percent of all projects approved by the Executive Board after 2019 list "climate change" as a sub-theme, only 12.6 percent list it as their main sub-theme. This raises concerns that the Bank could be inflating the number of projects coded as climate-adjacent to appear closer to reach climate funding goals.

In short, the two official taxonomies are incomplete and not comparable. Secondary labels, in particular, appear to reflect institutional priorities more than actual project content. As a result, it is difficult to say whether the World Bank has meaningfully shifted its lending patterns to prioritize climate over fossil fuel funding — perhaps it is simply overcounting the former and no longer counting the latter. 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 because projects do not always fit squarely into one sector. Since we are interested in one specific "hard" sector for which there might be an incentive to provide erroneous labels, we need more granular coding. For this reason, we validate the official classifications using text analysis.

Figure 3: World Bank Projects, by Theme, 2001–2022



This figure shows the distribution of World Bank projects across years (x-axis) and countries (y-axis, with labels removed for ease of visualization), highlighting projects with climate change as the main theme (top) or as any theme — primary or secondary (bottom). White cells indicate that the country in question did not receive any projects that year.

4.3 Validating the 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).[20] 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, 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), capturing the relative importance of different topics within one single project. This implementation has already been used to classify conditionality from the World Bank (Cormier and Manger, 2022) and the IMF (Goes, 2023). Topic models render this a particularly hard test: in rejecting sector 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. To do so, the model assumes that each document is a mixture of multiple topics and that each topic is a distribution of 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 how likely each word is to belong to a topic, given the word's 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. In identifying a set

[20] 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.

of topics, the model does not assign documents to topics; rather, it calculates the proportion of each document's vocabulary corresponding to a specific topic.

The most widely used topic modeling framework is the Latent Dirichlet Allocation model, or LDA (Blei, Ng and Jordan, 2003). One challenge with traditional topic models like the LDA is that they depend heavily 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 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 do not overlap as much. We estimate a dynamic keyATM, an extension of the model that uses a Hidden Markov Model to incorporate time ordering, allowing researchers to investigate how the prevalence of each topic changes over time.

Our dynamic keyATM has four pre-specified topics. The reference topic, *Health*, confirms that the top words associated with each topic define a meaningful theme, whereas *Extractives*, *Renewables*, and *Climate* mirror our sectors and themes of interest. In addition, ten residual topics with no keywords absorb content that does not fall under the four topics of interest.[21] Table 1 presents the top ten words for the pre-specified topics. The pre-specified keywords correctly matched to the pre-specified topic are in bold.

In Figure 4, each panel presents θ, the relative prevalence of a topic, averaged for all

[21] 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.

Table 1: Most Common Words Per Topic

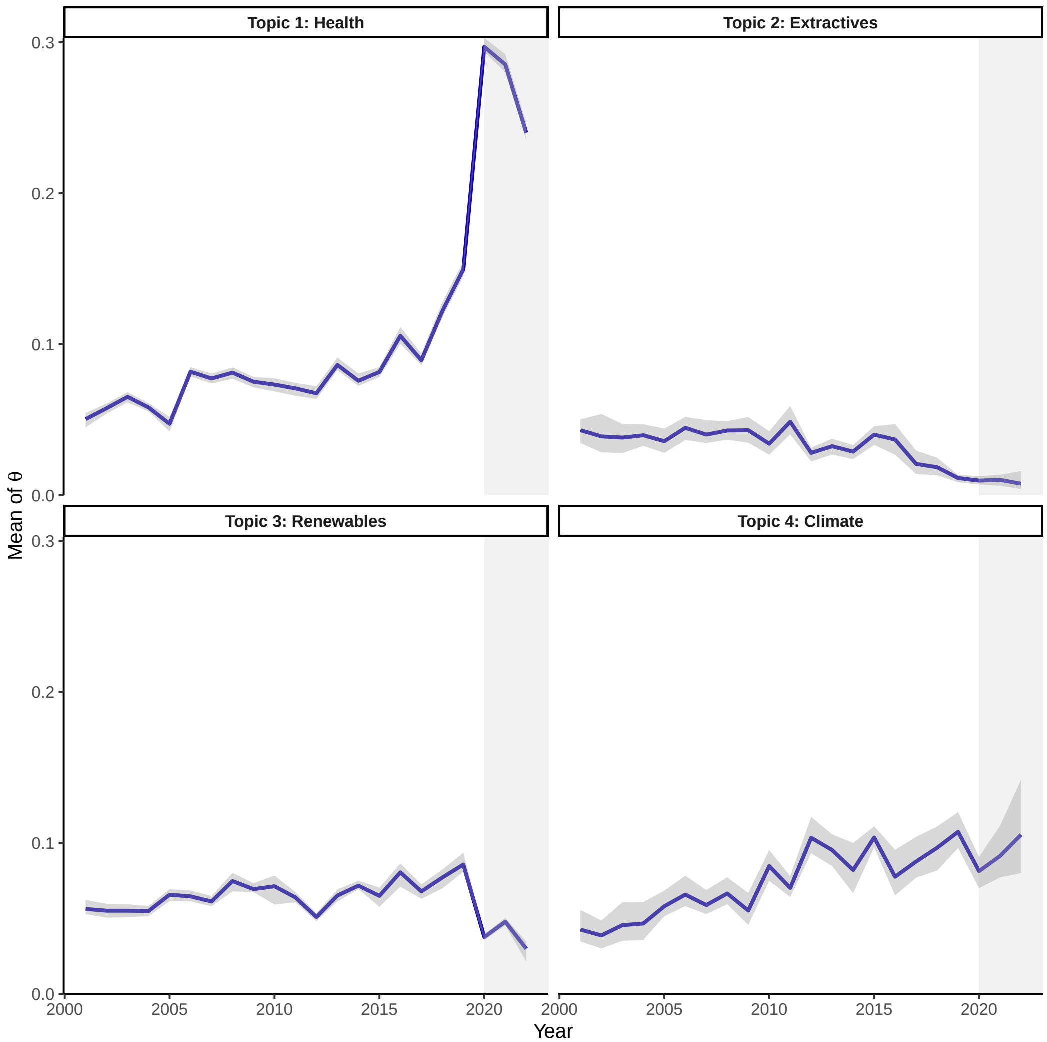
Topic 1: Health	Topic 2: Extractives	Topic 3: Renewables	Topic 4: Climate
health	**eiti**	energy	**climate**
covid-19	capacity	electricity	development
response	implementation	development	management
services	**gas**	power	resilience
emergency	**mining**	efficiency	**carbon**
development	government	increase	disaster
strengthen	national	**renewable**	natural
improve	technical	access	change
financing	**oil**	improve	sustainable
respond	support	supply	risk

projects approved by the Executive Board every year between 2001 and 2022. The post-2019 period is shaded in grey. For the average project approved in 2001, around five percent of the vocabulary was related to each of the four topics. Unsurprisingly, the vocabulary associated with the health sector increased sharply in 2020 and 2021, indicating that World Bank project priorities respond quickly to large-scale events like a global pandemic and again confirming that the model is doing a good job of parsing out different topics. No other sector experienced such a radical shock. Over time, there has been a gradual, consistent decline in *Extractives*, yet no abrupt change after 2019 — only a continuation of already existing trends. The vocabulary related to *Renewables* or *Climate* increased gradually until 2019, but declined in 2020. Overall, this provides suggestive evidence that the World Bank indeed reduced extractive funding after 2019, but only because it was already in the process of doing so, not as a direct result of an official pledge.

Beyond providing descriptive information, the purpose of the topic models is to validate the official World Bank classifications. These models are not intended to serve as a ground truth, as they rely on the vocabulary of official project documents, not on actual project implementation. Yet they provide an alternative means of assessing whether the official labels align with each project's title and description.

All topic proportions are positively and significantly correlated with their corresponding

Figure 4: 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 associated with a topic, averaged for all projects approved yearly, with 90 percent confidence intervals.

project sectors or themes ($p = 0.000$), indicating that the Bank's official classification generally reflects each project's content. However, there is considerable variation across issue areas.[22] While the correlations are large for health-related projects (e.g., $r = 0.72$ for *Topic: Health* and *Sector: Health*), the correlation between *Topic: Climate* and *Theme: Climate* is considerably smaller: $r = 0.39$ when climate change is the primary label and $r = 0.29$

[22]See Appendix E for a correlation matrix.

when climate change is any label (primary or secondary). Put differently, the Bank's climate change theme is significantly aligned with climate topics, yet the relationship is weaker than in other issue areas, which may reflect the broader application of the "climate" label to projects with only secondary climate relevance. As expected, there is a negative (and non-significant) correlation between extractive and renewable projects, whether these are measured in terms of project sectors or topic proportions.

5 Explaining Variation in World Bank Projects

5.1 Dependent Variables and Empirical Strategy

Like Cormier and Manger (2022), Clark and Dolan (2021), Kersting and Kilby (2016), and many others, our unit of analysis is a World Bank project.[23] Quasi-experimental approaches (like a difference-in-differences, a regression discontinuity design, or a generalized synthetic control) would be ideal to provide causal leverage, but are not feasible because the treatment is defined by a time-based event. No unit is treated until 2019, and all units are treated after 2019, so there is no natural control group. Given how much has changed in the world after 2019, it is not realistic to assume that both periods are directly comparable in every meaningful way *except for a shift in the World Bank's funding priorities.* Given these constraints, we adopt a simple empirical strategy.

First, we seek to explain variation in project *content*. When the dependent variables *Health*, *Extractives*, *Renewables*, and *Climate* are measured as sectors or themes, we estimate logistic regressions; when they are measured as continuous topic proportions, we estimate linear regressions. Second, the *size* of each project matters. Even if there is a decline in the frequency of extractive projects, for example (as Figure 2 suggests), this shift could be offset by increased funding for each extractive project. To assess this possibility, linear regressions examine each project's logged new IDA and IBRD commitments, deflated to

[23] Appendix I reports alternative models using country-year pairs as the unit of analysis.

billions of constant 2023 US dollars using the World Development Indicators' GDP deflator. We also weigh each project size against the total annual commitments, since the World Bank's overall lending capacity changes over time.[24] Finally, we use logistic regressions with duration-dependent dummy variables to examine a project's probability of ending at any given point in time. This event-history approach excludes about 600 projects for which the end date is unknown.

Following Cormier and Manger (2022), all models include standard errors clustered two ways, by country and year (with the exception of the event-history models, which only cluster standard errors by country). Two-way clustering allows for within-country correlation (as multiple projects in one country are often complementary) and within-year correlation (as the World Bank often approves similar projects across different countries in the same year).[25]

5.2 Independent Variables

Our main goal is to understand whether World Bank projects approved after 2019 are significantly different from prior projects, as indicated by the dichotomous variable *After 2019*. As Figures 2, 3, and 4 imply, this is likely not a "hard" cut-off: the Bank began to increased climate finance and phase out extractive finance much sooner. Therefore, we also experiment with other cut-offs in Appendix H.

Beyond temporal dynamics, existing research tends to focus on the number, size, and conditionality of World Bank projects, not their content. Yet project content, size, and duration are plausibly explained by similar factors: a mix of recipient conditions and donor interests (Cormier and Manger, 2022), lagged to avoid simultaneity bias.

Good governance affects the types of loans a country receives: poorly governed countries are less likely to receive DPF, which is broad, and more likely to receive IPF, which is narrow

[24]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.

[25]Appendix J reports alternative specifications with country fixed effects and standard errors clustered by country and year.

and project-specific (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 case of a recent drought, wildfire, flood, landslide, or earthquake, for example.

The recipient's logged *GDP per Capita* (in constant 2015 US dollars) and *Resource Rents* (in percentage of the GDP), both from the World Development Indicators 2024, likely affect project content: 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 a skewed distribution, we do not log them to prevent the loss of negative values (which are instances of loan repayment). 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, one dichotomous indicator denotes *IMF Program Participa-*

tion (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 until 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. US allies receive more projects (Dreher, Sturm and Vreeland, 2009*a*) with fewer conditions (Clark and Dolan, 2021), and if the Bank coordinates its activities with the Fund (Marchesi and Sirtori, 2011). 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 the "exceptional circumstance" category.

5.3 Explaining Project Content

Table 2 presents the results of six logistic regressions. In all but Model 6, the dependent variable is the project's *main* sector or theme, as classified by the World Bank. As a point of reference, Models 1 and 2 examine variation in the reference category, *Health*. The old sector-based classification and the new theme-based classification coincide: relative to a project approved between January 2001 and December 2019, the odds of an approved project belonging to the health sector tripled after 2019, reflecting a rapid response to the COVID-19 pandemic ($e^{1.224} = 3.401$ in Model 1; $e^{1.061} = 2.889$ in Model 2).

Turning to the categories of interest, the outcomes for Models 3 and 4 are derived from the Bank's older classification, which does not include a climate change sector. According to Model 3, the odds of an approved project belonging to *Sector: Extractives* decreased by nearly 84 percent after 2019 ($e^{-1.816} = 0.163$), which is consistent with the Bank's stated priorities. However, Model 4 shows that the same happened to *Sector: Renewables*: the odds for this sector decreased by 35 percent in the same period ($e^{-0.435} = 0.647$). Unsurprisingly, EITI members, SIDS, and countries with a large GDP share coming from resource rents are more likely to attract extractive projects, as are those under an IMF agreement, reflecting the IMF's interest in natural resource governance (Goes, 2023; Goes and Chapman, 2024)

— which might come at the expense of the environment (Forster, Bhandary and Gallagher, 2024). Meanwhile, renwewable projects are more prevalent among UNSC members and DAC aid recipients, all else equal.

Table 2: Predictors of Project Sector and Theme, 2001–2022

	Dependent Variable:					
	Sector: Health (1)	Theme: Health (2)	Sector: Extractives (3)	Sector: Renewables (4)	Theme: Climate (5)	Theme: Climate (Any) (6)
After 2019	1.224***	1.061***	−1.816***	−0.435***	0.218	2.506***
	(0.105)	(0.081)	(0.211)	(0.086)	(0.167)	(0.390)
Governance	−0.171*	−0.118	−0.285	0.242	0.325**	0.172
	(0.094)	(0.075)	(0.216)	(0.197)	(0.139)	(0.141)
Election Year	−0.031	−0.025	0.278	−0.079	−0.066	−0.003
	(0.097)	(0.076)	(0.202)	(0.149)	(0.083)	(0.100)
EITI Member	−0.015	−0.151*	1.267***	−0.188	0.090	0.632***
	(0.062)	(0.079)	(0.221)	(0.250)	(0.149)	(0.232)
Field Discovery	−0.306**	−0.101	−0.030	−0.194	0.403**	0.171
	(0.154)	(0.191)	(0.323)	(0.249)	(0.167)	(0.191)
SIDS	0.033	−0.191***	0.798***	0.141	0.228	0.236
	(0.127)	(0.051)	(0.301)	(0.240)	(0.213)	(0.149)
Disaster	0.005	−0.102	0.041	−0.023	0.229**	0.070
	(0.094)	(0.090)	(0.172)	(0.124)	(0.107)	(0.097)
Log GDP per Capita	−0.081	0.109*	0.168*	−0.059	0.322***	0.091
	(0.059)	(0.058)	(0.099)	(0.108)	(0.099)	(0.096)
Log Resource Rents	0.040	0.040	0.279**	−0.003	0.003	−0.054
	(0.026)	(0.028)	(0.115)	(0.050)	(0.034)	(0.042)
DAC Aid	−0.107*	0.002	0.034	0.072***	0.041	0.040
	(0.064)	(0.035)	(0.034)	(0.019)	(0.045)	(0.058)
Chinese Finance	0.011**	0.006	−0.050*	−0.007	−0.004	0.009
	(0.005)	(0.010)	(0.029)	(0.013)	(0.013)	(0.017)
IMF Program	0.047	0.018	0.294*	−0.098	−0.315***	−0.405***
	(0.063)	(0.069)	(0.178)	(0.140)	(0.112)	(0.099)
UNSC Member	0.114	−0.069	0.034	0.268**	0.022	−0.155
	(0.102)	(0.087)	(0.216)	(0.131)	(0.190)	(0.160)
Voting with the US	−1.177***	−0.998**	0.417	−1.273	0.045	1.407
	(0.324)	(0.460)	(1.452)	(1.055)	(0.736)	(1.125)
Intercept	−1.835***	−3.116***	−6.600***	−2.410***	−4.945***	−2.143***
	(0.470)	(0.468)	(0.904)	(0.883)	(0.755)	(0.707)
Observations	9680	9680	9680	9680	9680	9680
AIC	5715.6	5927.5	1504.8	2962.9	5505.2	9868.0

This table presents the results of six logistic regressions with standard errors clustered by country and year. The dependent variable indicates whether *Health*, *Extractives*, *Renewables*, or *Climate* is the project's main sector or theme, except for Model 6, whose dependent variable indicates whether *Climate* is either the project's main or its secondary theme. Other than *After 2019*, all independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

The last two models in Table 2 follow the new taxonomy, which includes climate change as a sub-theme of *Environment and Natural Resource Management* (with no corresponding category for extractive industries or renewable energy generation). Since the World Bank might inflate the number of climate-related projects to meet its institutional priorities, we distinguish between projects with climate as the *main* theme and as *any* theme (Models 5 and 6, respectively). After 2019, there was no significant increase in the odds of approving a project with climate as the *main* theme. However, the odds of approving a project with climate as *any* theme — primary or secondary — increased over 12-fold, according to Model 6 ($e^{2.506} = 12.256$).

The World Bank warns that the new taxonomy is not comparable for the pre-2016 and post-2016 periods, so these results should be viewed with caution. Still, they are robust to the exclusion of the pre-2016 period. In fact, an analysis of the 2016–2022 period in Appendix G shows that the number of projects with climate as the main theme *decreased* significantly after 2019, whereas the number of projects with climate as any theme *increased* significantly.

Though the World Bank promised to stop funding upstream oil and gas *by 2019*, Figures 2, 3, and 4 already suggested that this was likely not a "hard" cut-off, as the Bank was already phasing out extractive industries from its project vocabulary. Correspondingly, Appendix H presents models with other years as a cut-off, finding that the results hold when *After 2019* is replaced with *After 2017*, *After 2018*, or *After 2020*. On the one hand, this is encouraging: it means that the World Bank has gradually shifted its portfolio, funding climate-related projects while reducing its propensity to support extractive-sector initiatives. On the other hand, it means that the pledge to phase out oil and gas funding after 2019 was cheap and toothless, as the Bank was already in the process of doing so anyway.[26]

Given the discrepancy between Models 5 and 6, one might wonder: which classification is "right?" Is a focus on the *main* theme too narrow? Or is it too generous to consider *all* themes? To validate the official classification, Table 3 turns to the topic proportions.

[26] Table 3 measures the odds that an approved project will belong to each sector or theme, not the number of projects. Appendix I examines the latter, finding that the total number of projects per country displays similar patterns. The recent increase in the number of climate projects per country and year, while significant, is much less pronounced when only the main sector is taken into account.

A project approved after December 2019 used 0.193 percent more words related to health (Model 1), 2.5 percent fewer words related to extractives (Model 2), and 2.6 percent fewer words related to renewables (Model 3). Whereas these effects are statistically significant, there were no significant changes in the climate vocabulary after 2019.[27] These results coincide with those for the main sectors or themes in Table 2. Even the control variables behave similarly. For example, EITI membership and resource rents are associated with higher odds of a project belonging to the extractive sector *and* a higher topic proportion for extractives; oil and gas field discoveries are associated with lower odds of belonging to the health sector *and* a smaller topic proportion for health; higher governance is associated with more projects in the climate theme *and* a higher topic proportion for the climate. The similarities between Tables 2 and 3 suggest that the World Bank codes its projects accurately. In other words, the official classification truly matches the vocabulary used to describe these projects — at least when it comes to the *main* category.

In contrast, looking at *all* themes risks overstating climate funding after 2019: though the "climate" label was assigned more generously in recent years, the actual content of projects did not reflect such change. To reiterate, the topic proportions rely on the vocabulary of official project documents, not on actual implementation. The broader classification could be right, and the topic proportions could be wrong: projects could include a "hidden" climate component despite not explicitly mentioning such a component in the project summary. But 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 at all related to climate change, then the project description should mention this — and the topic proportion should capture it. The absence of a significant effect for *After 2019* in Model 4 of Table 3 suggests that recent projects are less climate-centric than the World Bank's taxonomy might initially suggest.

[27] Appendix F presents similar models for the remaining topics.

Table 3: Predictors of Topic Proportions, 2001–2022

	Dependent Variable:			
	Topic: Health (%)	Topic: Extractives (%)	Topic: Renewables (%)	Topic: Climate (%)
	(1)	(2)	(3)	(4)
After 2019	0.193***	−2.500***	−2.647***	0.469
	(0.014)	(0.355)	(0.494)	(0.619)
Governance	−0.042***	0.229	0.807	2.561***
	(0.010)	(0.347)	(0.920)	(0.806)
Election Year	−0.005	0.589***	0.287	−0.668
	(0.004)	(0.224)	(0.545)	(0.508)
EITI Member	0.005	0.810**	−0.223	0.753
	(0.009)	(0.412)	(0.599)	(0.757)
Field Discovery	−0.027***	−0.363	−0.421	1.263
	(0.010)	(0.359)	(0.929)	(0.834)
SIDS	0.022	0.199	−1.511	5.263***
	(0.014)	(0.514)	(1.122)	(1.941)
Disaster	−0.001	0.192	−1.040*	1.806***
	(0.009)	(0.292)	(0.620)	(0.525)
Log GDP per Capita	−0.007	0.326*	−0.769	0.757*
	(0.006)	(0.196)	(0.497)	(0.415)
Log Resource Rents	−0.005**	0.326***	−0.138	−0.060
	(0.002)	(0.092)	(0.247)	(0.251)
DAC Aid	−0.007*	0.170	0.324	0.151
	(0.004)	(0.116)	(0.243)	(0.170)
Chinese Finance	0.001	−0.002	0.058	−0.075
	(0.001)	(0.026)	(0.045)	(0.060)
IMF Program	0.007	0.204	−0.811*	−2.455***
	(0.008)	(0.294)	(0.478)	(0.544)
UNSC Member	−0.003	−0.213	−1.190*	0.057
	(0.011)	(0.453)	(0.655)	(0.805)
Voting with the US	−0.043	0.481	3.834	−3.838
	(0.037)	(2.210)	(3.919)	(3.871)
Intercept	0.125***	−0.523	13.586***	2.073
	(0.048)	(1.688)	(4.234)	(3.274)
Observations	9680	9680	9680	9680
R^2	0.080	0.011	0.004	0.023

This table presents the results of four linear regressions with standard errors clustered by country and year. The dependent variable is the prevalence of the corresponding topic, converted to a percentage. Other than *After 2019*, all independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

5.4 Explaining Project Commitments

According to Table 2, the odds of a World Bank project being primarily classified under the extractive and renewable sectors decreased significantly after 2019, a decrease mirrored by the corresponding topic proportions in Table 3. A generous definition of "climate project" (i.e., one that encompasses projects with climate change as their main or secondary theme)

Table 4: Predictors of Project Commitments, 2001–2022

	Dependent Variable:					
	Log USD	% Total	Log USD	% Total	Log USD	% Total
	(1)	(2)	(3)	(4)	(5)	(6)
After 2019	0.805***	−0.019	0.897***	−0.017	−0.285	−0.002
	(0.136)	(0.018)	(0.132)	(0.019)	(0.213)	(0.111)
Sector: Extractives	−3.448***	−0.132***				
	(0.521)	(0.037)				
Sector: Extractives × After 2019	2.176	0.409				
	(1.775)	(0.326)				
Sector: Renewables	−1.842***	0.030				
	(0.431)	(0.059)				
Sector: Renewables × After 2019	1.646***	−0.004				
	(0.455)	(0.076)				
Theme: Climate			−1.071***	−0.078**		
			(0.305)	(0.032)		
Theme: Climate × After 2019			0.666	0.038		
			(0.407)	(0.032)		
Theme: Climate (Any)					0.219	0.022
					(0.293)	(0.030)
Theme: Climate (Any) × After 2019					1.396***	−0.031
					(0.356)	(0.131)
Governance	0.061	0.021	0.088	0.024	0.043	0.022
	(0.144)	(0.035)	(0.148)	(0.035)	(0.142)	(0.035)
Election Year	−0.007	−0.014	−0.022	−0.015	−0.022	−0.015
	(0.091)	(0.018)	(0.094)	(0.018)	(0.092)	(0.018)
EITI Member	0.015	−0.020	−0.063	−0.023	−0.100	−0.026
	(0.129)	(0.027)	(0.150)	(0.027)	(0.135)	(0.027)
Field Discovery	0.434***	0.087***	0.493***	0.090***	0.442***	0.086***
	(0.126)	(0.030)	(0.126)	(0.030)	(0.118)	(0.030)
SIDS	−0.823***	−0.168***	−0.857***	−0.168***	−0.900***	−0.170***
	(0.127)	(0.026)	(0.131)	(0.026)	(0.137)	(0.026)
Disaster	0.371***	0.076***	0.394***	0.077***	0.377***	0.076***
	(0.126)	(0.026)	(0.126)	(0.026)	(0.125)	(0.026)
Log GDP per Capita	0.018	0.041*	0.034	0.043*	0.013	0.041*
	(0.085)	(0.024)	(0.090)	(0.024)	(0.087)	(0.024)
Log Resource Rents	−0.027	0.008	−0.036	0.008	−0.034	0.008
	(0.035)	(0.007)	(0.036)	(0.007)	(0.033)	(0.007)
DAC Aid	0.153**	0.024	0.141*	0.024	0.135*	0.024
	(0.077)	(0.016)	(0.078)	(0.016)	(0.073)	(0.016)
Chinese Finance	0.024***	0.005***	0.026***	0.005***	0.027***	0.005***
	(0.009)	(0.001)	(0.009)	(0.001)	(0.008)	(0.001)
IMF Program	−0.126	−0.016	−0.159	−0.018	−0.120	−0.015
	(0.113)	(0.029)	(0.116)	(0.029)	(0.106)	(0.028)
UNSC Member	0.256***	0.086***	0.234***	0.086***	0.245***	0.087***
	(0.084)	(0.026)	(0.083)	(0.025)	(0.075)	(0.026)
Voting with the US	0.508	0.266	0.575	0.263	0.522	0.257
	(0.737)	(0.227)	(0.726)	(0.225)	(0.724)	(0.226)
Intercept	16.581***	−0.198	16.442***	−0.202	16.461***	−0.197
	(0.736)	(0.216)	(0.776)	(0.217)	(0.744)	(0.215)
Observations	9680	9680	9680	9680	9680	9680
R^2	0.081	0.035	0.053	0.035	0.053	0.034

This table presents the results of six linear regressions with standard errors clustered by country and year. The dependent variable indicates the total amount of IDA/IBRD commitments to each project, in logged billions of 2023 USD (Models 1, 3, and 5) or as a percentage of total IDA/IBRD commitments (Models 2, 4, and 6). Other than *After 2019* and the sectors or themes, all independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

would suggest an increased climate focus after 2019. However, a stricter definition (i.e., one that considers the vocabulary of project descriptions or only projects with climate change as the main theme) would conclude that there was only a modest change in recent years.

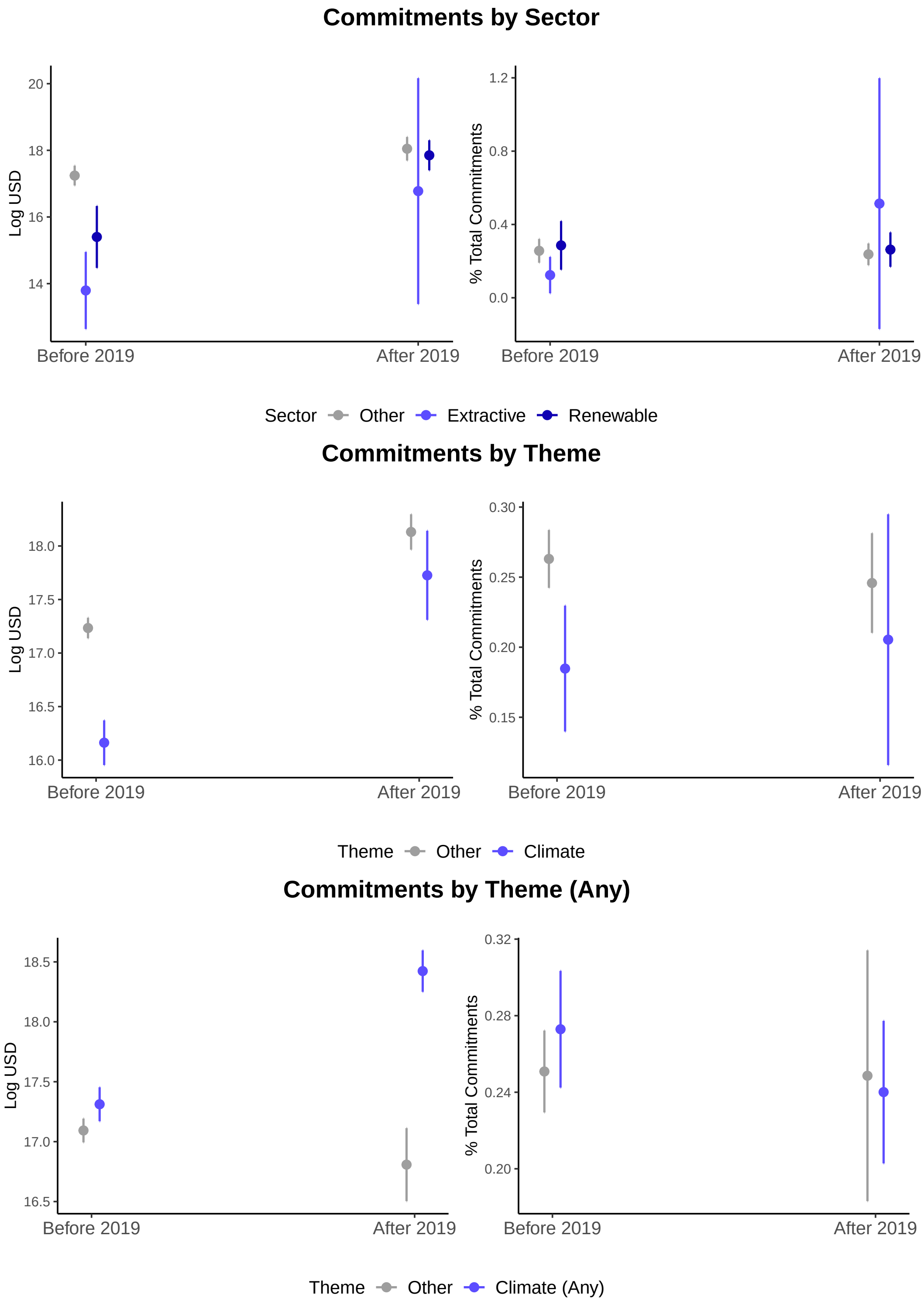
Even if fewer projects are coded as belonging to the extractive and renewable sectors after 2019, it is possible that each project is larger: it mobilizes more resources. To test for this possibility, Table 4 turns to new IDA and IBRD commitments per project, either in absolute terms (in logged US dollars) or in relative terms (as a percentage of total annual commitments). Models 1 and 2 examine these commitments by main sector, with the top panels of Figure 5 visualizing the results.

In absolute terms (Model 1), the average World Bank project approved after 2019 attracted more funding, no matter the sector, though only renewable energy projects attracted *significantly* more funding. Put differently, the odds of a project belonging to the renewable sector declined if such project was approved after 2019, yet the World Bank appears to be consolidating resources into fewer, larger initiatives in this sector, reflecting a strategic choice to fund high-impact renewable projects. Still, when sector-specific commitments are weighted against total IDA and IBRD commitments, there is no significant change in project-specific funding (Model 2). This suggests that the relative importance of each individual project, in budgetary terms, did not change for any sector after 2019: each extractive or renewable project continues to receive a similar slice of the total pie.

In Table 4, Models 3 and 4 examine the commitments by main theme, with the middle panels of Figure 5 visualizing the results. The average project with climate change as the main theme was always significantly smaller than the average project with other main themes, a dynamic that did not change after 2019. Finally, Models 5 and 6 examine the commitments by *any* theme (corresponding to the bottom panels of Figure 5). In absolute terms, compared to the 2001–2019 period, projects with climate change as *any* theme — main or secondary — attracted over three times more funding after 2019 ($e^{-0.285+0.219+1.396-0.219} = e^{1.111} = 3.037$).[28]

[28]Since the outcome is logged, we can exponentiate the coefficients to interpret the multiplicative changes in funding.

Figure 5: Predictors of Project Commitments: Interactions, 2001–2022



This plot displays IDA/IBRD commitments to each project, with 95 percent confidence intervals, by main sector (top panels, based on Models 1 and 2 of Table 4); main theme (middle panels, based on Models 3 and 4 of Table 4); and any theme — main or secondary (bottom panels, based on Models 5 and 6 of Table 4).

However, there was no change in relative terms. Assuming the overall size of the Bank's lending portfolio increased after 2019, climate projects grew proportionally. The odds of observing such a project might be higher, but each project continues to attract an equivalent amount of funding. Appendix I shows the results aggregated by country and year, confirming that the total amount of climate funding for the average country increased significantly after 2019, while the total amount of extractive funding declined slightly in the same period.

5.5 Explaining Project End

As a final step, we use event-history models to estimate the probability that a project ends at a given point in time, conditional on it not having ended previously. Specifically, we estimate logistic regressions with duration-dependent dummies (Beck, Katz and Tucker, 1998). This discrete-time approach, while conceptually similar to a Cox proportional hazard model, is easier to estimate and yields logit coefficients that can be easily visualized and interpreted in terms of odds ratios.[29] Table 5 presents the results, with Figure 6 visualizing the corresponding interactions between *After 2019* and the project sectors or themes.

Model 1 shows that at any given year, extractive projects are significantly more likely to end than projects in other sectors. This effect is particularly pronounced after 2019, as indicated by the positive and statistically significant interaction between *Sector: Extractives* and *After 2019*. Turning to climate-focused initiatives, Models 2 and 3 suggest that such projects follow the opposite dynamic: they are generally less likely to end, but their "survival advantage" (relative to other sectors) diminishes after 2019.

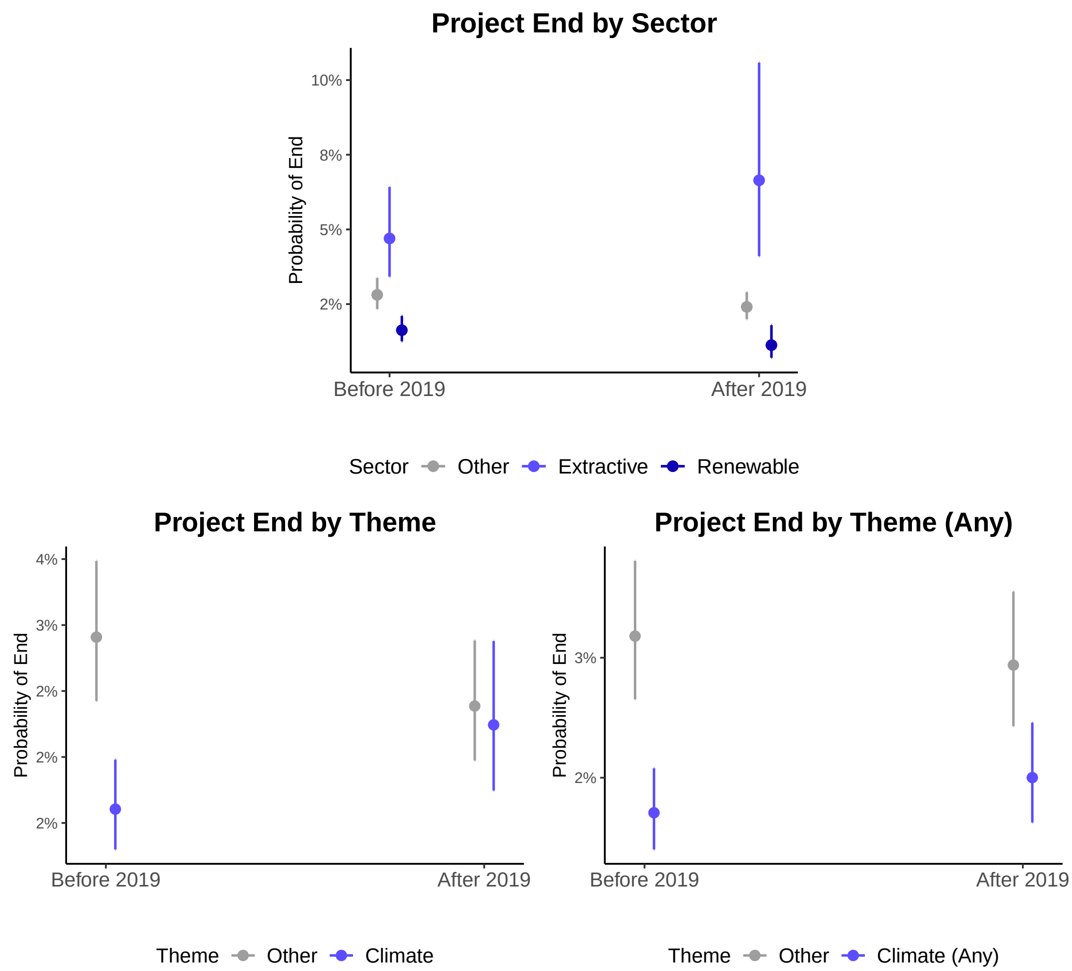
[29] Appendix K presents Cox proportional hazard models that corroborate the main results.

Table 5: Predictors of Project End, 2001–2022

	Dependent Variable:		
	Probability of End	Probability of End	Probability of End
	(1)	(2)	(3)
After 2019	−0.159***	−0.203***	−0.080
	(0.059)	(0.060)	(0.069)
Sector: Extractives	0.534***		
	(0.139)		
Sector: Extractives × After 2019	0.526**		
	(0.220)		
Sector: Renewables	−0.559***		
	(0.113)		
Sector: Renewables × After 2019	−0.214		
	(0.248)		
Theme: Climate		−0.608***	
		(0.065)	
Theme: Climate × After 2019		0.545***	
		(0.117)	
Theme: Climate (Any)			−0.638***
			(0.052)
Theme: Climate (Any) × After 2019			0.241***
			(0.090)
Governance	0.034	0.039	0.054
	(0.071)	(0.070)	(0.070)
Election Year	0.039	0.036	0.025
	(0.036)	(0.036)	(0.035)
EITI Member	0.124*	0.146**	0.166***
	(0.065)	(0.064)	(0.063)
Field Discovery	0.151*	0.168**	0.176**
	(0.080)	(0.076)	(0.073)
SIDS	0.161**	0.162**	0.177**
	(0.069)	(0.068)	(0.069)
Disaster	−0.059	−0.057	−0.056
	(0.043)	(0.042)	(0.042)
Log GDP per Capita	−0.060*	−0.046	−0.048
	(0.036)	(0.036)	(0.037)
Log Resource Rents	−0.026	−0.025	−0.027
	(0.016)	(0.017)	(0.017)
DAC Aid	−0.065*	−0.064*	−0.061*
	(0.034)	(0.035)	(0.035)
Chinese Finance	−0.007	−0.007	−0.008
	(0.006)	(0.006)	(0.006)
IMF Program	0.079	0.071	0.053
	(0.051)	(0.050)	(0.051)
UNSC Member	−0.010	−0.013	−0.021
	(0.061)	(0.060)	(0.061)
Voting with the US	0.470*	0.501**	0.588**
	(0.244)	(0.247)	(0.251)
Intercept	−3.003***	−3.080***	−2.982***
	(0.327)	(0.322)	(0.331)
Observations	49 109	49 109	49 009
AIC	36 693.9	36 681.8	36 421.7

This table presents the results of three logistic regressions with standard errors clustered by country and duration-dependent dummy variables. The dependent variable indicates the probability of a project ending at a given point, conditional on not having ended previously. Other than *After 2019* and the sectors or themes, all independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Figure 6: Predictors of Project End: Interactions, 2001–2022



This plot displays the predicted probability of event occurrence (project ending) each year, with 95 percent confidence intervals, averaged across each time interval, by main sector (top panel, based on Model 1 of Table 5); main theme (bottom left panel, based on Model 2 of Table 5); and any theme — main or secondary (bottom right panel, based on Model 3 of Table 5).

6 Conclusion

This study shows that World Bank projects are significantly less likely to belong to the oil and gas sector after 2019. While projects belonging to this sector tend to attract the same amount of funding, they are more likely to be end than before. This aligns with the global trend toward reducing fossil fuel dependency, suggesting that the Bank is becoming more selective about supporting extractive projects while still concentrating funding on a few abbreviated high-impact projects. True to its word, the Bank continues to fund such projects in exceptional circumstances.

Projects funded after 2019 are significantly more likely to be climate-related, particularly if we adopt a generous definition of “climate” that includes projects with climate as the secondary label. Each of these climate-related projects tends to attract more funding in absolute terms, with no significant change in relative terms. In the aggregate (see Appendix I), the World Bank is spending more on climate issues than before — not by funding larger climate projects, but by funding more such projects of the same size.

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 pushes 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. Future research will benefit from a mixed-methods approach that combines quantitative analysis with case studies of specific projects, like Guyana’s, to better understand IOs’ climate norms as well as instances of norm deviation. This approach will allow for a more nuanced interpretation of the World Bank’s evolving climate policies and their implications for global energy transitions. Additional studies can also distinguish between upstream and downstream finance or turn to IFC projects in the private sector, which are gradually (if selectively) being disclosed in recent years. Ultimately, 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 and Creative Accounting: How International Organizations Navigate Conflicting Demands

May 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-keywords 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 hyper parameters is not important — with the exception of π_{z_n}, which controls the weight of keywords and has a non-informative prior, $\text{Beta}(1, 1)$.

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, charcoal, extractive, extractives, diesel, fossil, fuel, hydrocarbon, lpg, mining, mine, mineral, minerals

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

Climate: climate, ghg, hcfc, hydrochlorofluorocarbons, 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

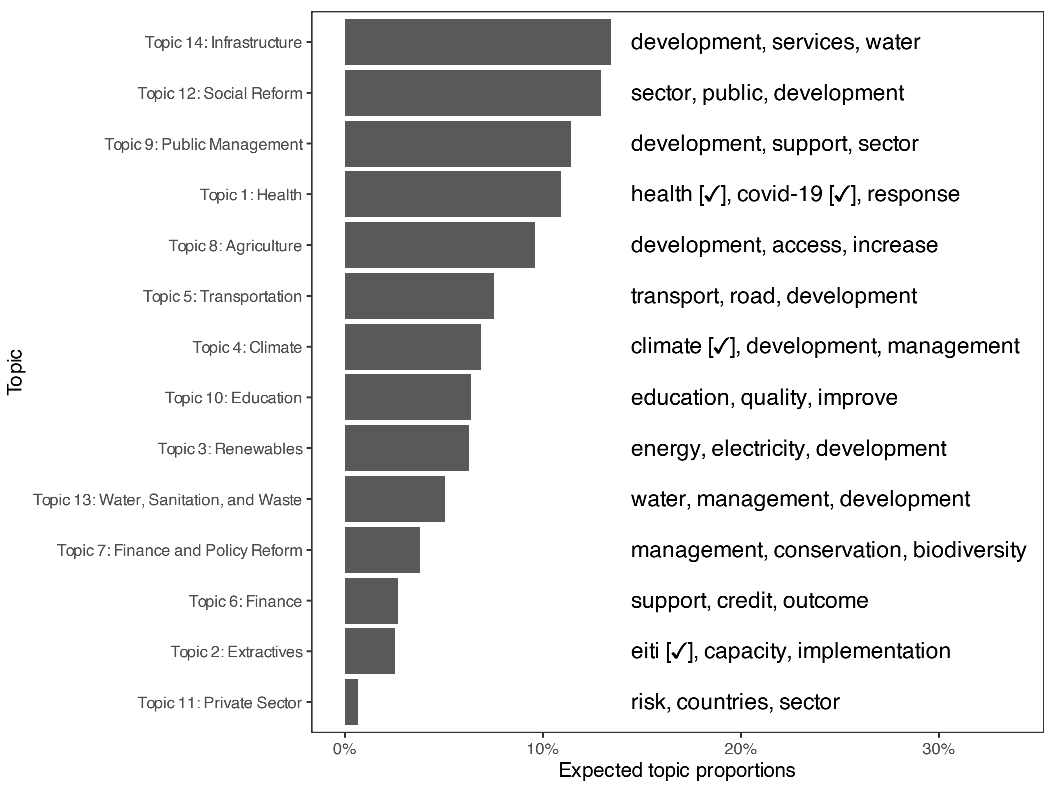
Table D.1 presents the ten most frequent words for all ten non-keyword topics. Though these topics are all "residual" (meaning the model identified them on its own, without any researcher input), we assigned post-hoc labels for ease of interpretation. Figure D.1 shows the expected proportion of the corpus belonging to each topic. In Figure D.2, each panel presents θ, the relative prevalence of these topics. The values of θ are averaged for all projects approved by the Executive Board every year between 2001 and 2022. The post-2019 period is shaded in grey.

Table D.1: Most Common Words Per Topic

Topic 5: Transportation	Topic 6: Finance	Topic 7: Environment	Topic 8: Agriculture	Topic 9: Public Management
transport	support	management	development	development
road	credit	conservation	access	support
development	outcome	biodiversity	increase	sector
improve	government	sustainable	rural	public
capacity	borrower	development	agricultural	policy
national	lessons	areas	improve	management
statistical	risk	forest	services	growth
data	poverty	environmental	support	government
urban	moderately	protected	agriculture	economic
roads	risk	communities	food	fiscal

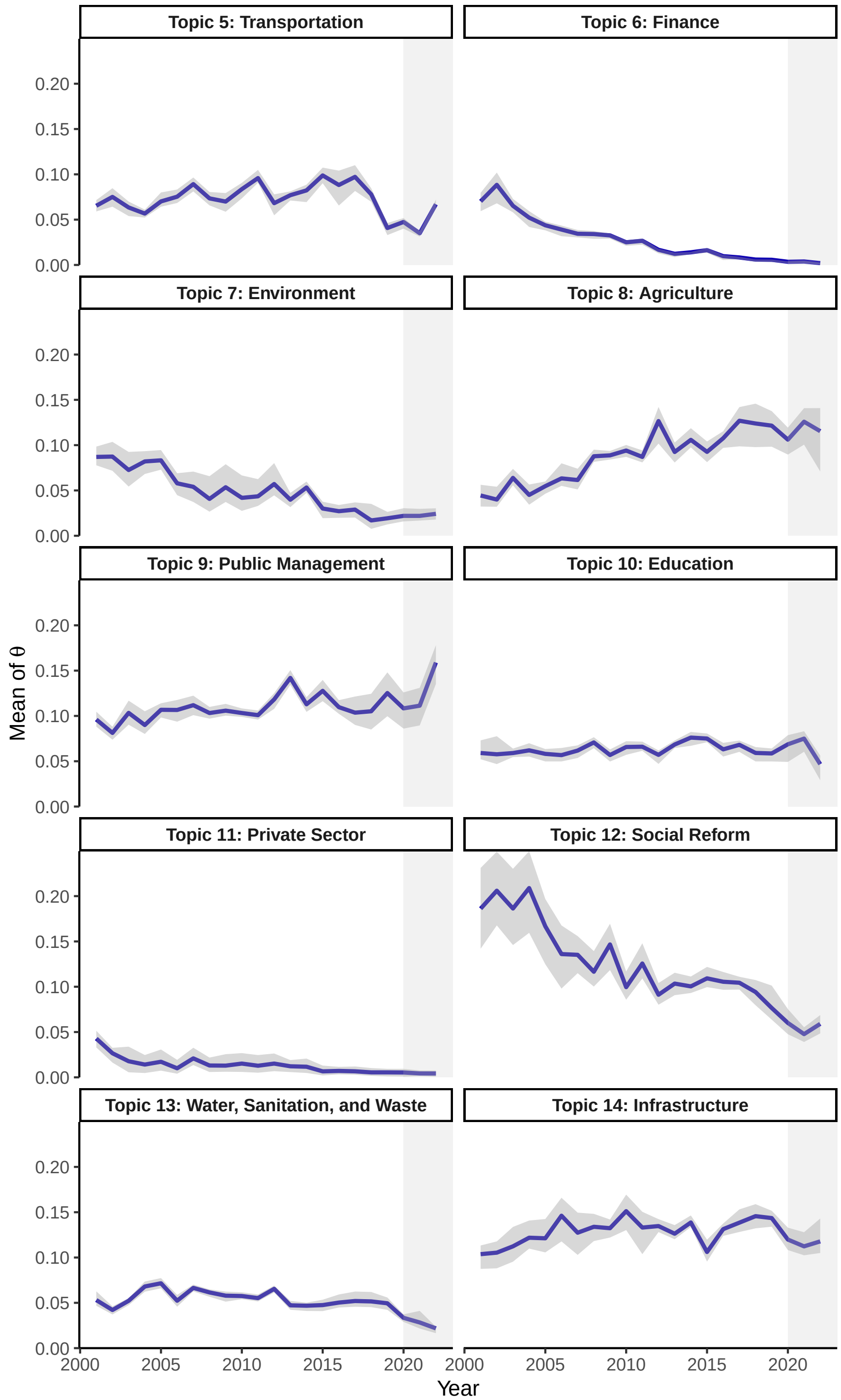
Topic 10: Education	Topic 11: Private Sector	Topic 12: Social Reform	Topic 13: Water, Sanitation, and Waste	Topic 14: Infrastructure
education	risk	sector	water	development
quality	countries	public	management	services
improve	sector	development	development	water
development	private	management	improve	access
learning	political	financial	irrigation	improve
access	insurance	support	land	rural
primary	activities	reform	services	local
secondary	available	policy	river	urban
school	trade	social	urban	social
schools	regional	improve	waste	infrastructure

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.

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



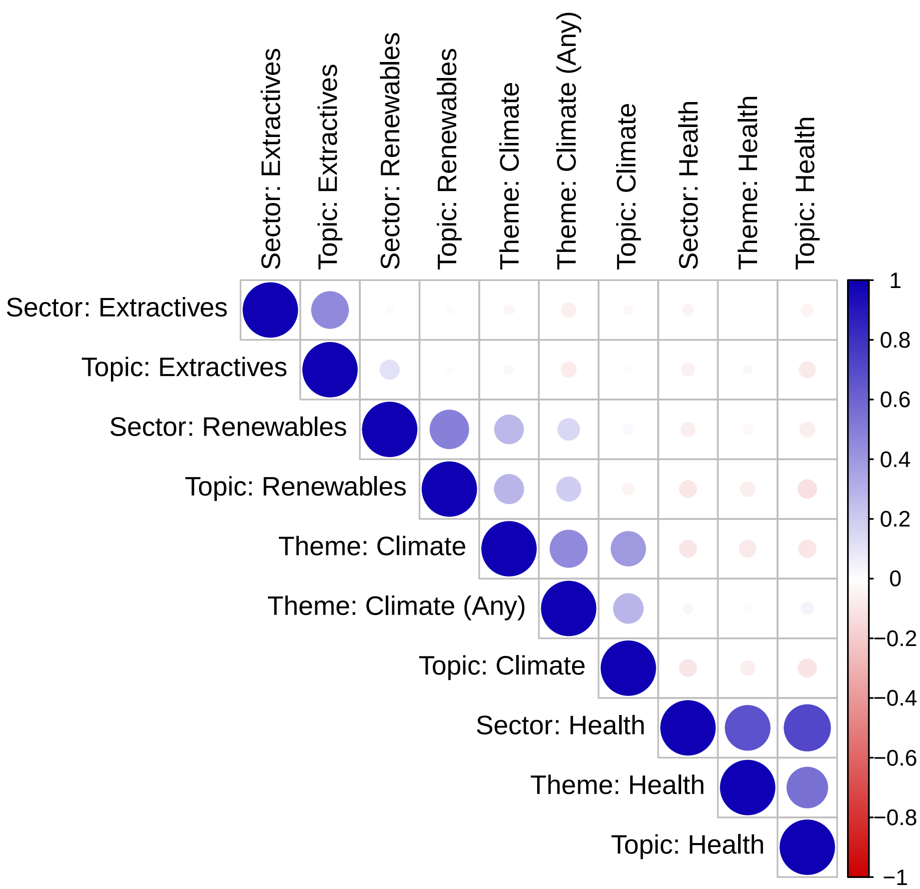
This plot displays the prevalence of each topic over time. The x-axis represents the year of project approval by the World Bank Executive Board. The y-axis represents θ, the proportion of words in each project description that are associated with a topic, averaged for all projects approved each year,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

E Summary Statistics

Table E.1: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Sector: Health	9680						
... 0	8791	90.82%					
... 1	889	9.18%					
Theme: Health	9680						
... 0	8765	90.55%					
... 1	915	9.45%					
Topic: Health	9680	0.1091	0.2715	0.000007018	0.000287	0.0008796	0.9996
Sector: Extractives	9680						
... 0	9524	98.39%					
... 1	156	1.61%					
Topic: Extractives	9680	0.02536	0.1041	0.000007018	0.0002788	0.0006471	0.991
Sector: Renewables	9680						
... 0	9338	96.47%					
... 1	342	3.53%					
Topic: Renewables	9680	0.06275	0.2065	0.000007018	0.0002711	0.0006471	0.9994
Theme: Climate	9680						
... 0	8842	91.34%					
... 1	838	8.66%					
Theme: Climate (Any)	9680						
... 0	6685	69.06%					
... 1	2995	30.94%					
Topic: Climate	9680	0.06859	0.2009	0.000007018	0.000287	0.0007457	0.9994
Commitments, Log USD	9680	17.14	2.657	-4.377	16	18.75	24.34
Commitments, % Total	9680	0.2273	0.5657	0	0.01632	0.242	31.61
After 2019	9680						
... 0	8181	84.51%					
... 1	1499	15.49%					
Governance	9680	-0.5414	0.5188	-2.221	-0.8641	-0.2179	1.328
Election Year	9680						
... 0	7217	74.56%					
... 1	2463	25.44%					
EITI Member	9680						
... 0	7569	78.19%					
... 1	2111	21.81%					
Field Discovery	9680						
... 0	8288	85.62%					
... 1	1392	14.38%					
SIDS	9680						
... 0	8848	91.4%					
... 1	832	8.6%					
Disaster	9680						
... 0	1898	19.61%					
... 1	7782	80.39%					
Log GDP per Capita	9680	7.567	0.958	5.533	6.825	8.274	10.35
Log Resource Rents	9680	1.177	1.586	-6.591	0.3616	2.281	4.375
DAC Aid	9680	0.7162	1.117	-0.7853	0.1554	0.9874	27.28
Chinese Finance	9680	1.193	4.089	0	0	0.6045	65.69
IMF Program	9680						
... 0	5664	58.51%					
... 1	4016	41.49%					
UNSC Member	9680						
... 0	9002	93%					
... 1	678	7%					
Voting with the US	9680	0.167	0.08999	0	0.1094	0.1948	0.8462

Figure E.1: Correlation Plot



This plot displays the correlation between different measurements of a project's extractive, renewable, climate, and health content.

F Additional Topics: Predictors

Table F.1: Predictors of Topic Proportions, 2001–2022

	Dependent Variable:									
	Topic: Transportation	Topic: Finance	Topic: Environment	Topic: Agriculture	Topic: Public Management	Topic: Education	Topic: Private Sector	Topic: Social Reform	Topic: Water, Sanitation, and Waste	Topic: Infrastructure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
After 2019	−2.902***	−2.454***	−1.643***	3.040***	2.383*	0.688	−0.467***	−8.885***	−2.163***	−2.231***
	(0.915)	(0.434)	(0.341)	(0.634)	(1.197)	(0.577)	(0.123)	(1.242)	(0.362)	(0.749)
Governance	0.617	1.124**	1.664***	−0.861	2.054	0.137	−0.065	0.951	−1.642	−3.337***
	(0.916)	(0.406)	(0.565)	(1.137)	(1.318)	(0.632)	(0.189)	(1.220)	(1.062)	(1.090)
Election Year	0.881	0.148	−0.501	0.351	0.496	0.248	−0.100	0.963	−0.891	−1.253
	(0.615)	(0.249)	(0.359)	(0.484)	(0.558)	(0.305)	(0.060)	(0.738)	(0.721)	(0.754)
EITI Member	−0.433	−1.399**	−1.083*	2.561*	0.624	1.200**	−0.388	−2.588*	−1.606**	1.302
	(0.573)	(0.531)	(0.528)	(1.283)	(1.024)	(0.426)	(0.230)	(1.462)	(0.674)	(0.961)
Field Discovery	1.578	−0.314	0.825	−1.805**	−1.666	−0.121	−0.157	0.207	3.298	0.398
	(1.600)	(0.352)	(0.745)	(0.807)	(1.069)	(0.841)	(0.136)	(1.570)	(2.138)	(2.309)
SIDS	0.260	0.509	−0.864	−1.405	2.843	0.303	−0.038	−2.084	−3.950***	−1.723
	(1.160)	(0.525)	(1.154)	(1.978)	(2.115)	(1.311)	(0.244)	(1.656)	(0.830)	(1.655)
Disaster	−0.076	0.250	0.577	−0.484	−1.295	0.168	0.019	−0.780	−0.471	1.268
	(0.661)	(0.270)	(0.548)	(0.965)	(0.807)	(0.575)	(0.176)	(1.056)	(0.815)	(0.996)
Log GDP per Capita	0.417	−0.428*	0.227	−1.184*	0.235	−0.452	−0.142	0.821	1.519*	−0.659
	(0.585)	(0.244)	(0.359)	(0.649)	(0.761)	(0.401)	(0.159)	(0.804)	(0.769)	(0.608)
Log Resource Rents	0.083	0.028	0.216	0.102	−0.061	−0.317	0.022	0.335	−0.051	0.019
	(0.207)	(0.112)	(0.188)	(0.287)	(0.392)	(0.209)	(0.033)	(0.320)	(0.173)	(0.378)
DAC Aid	0.390*	−0.063	−0.242*	0.140	−0.501	0.399*	−0.076	0.174	−0.099	−0.054
	(0.212)	(0.200)	(0.134)	(0.421)	(0.322)	(0.209)	(0.048)	(0.508)	(0.204)	(0.099)
Chinese Finance	0.026	−0.045*	0.007	0.079	−0.090	−0.057*	0.010	−0.109	−0.062	0.180*
	(0.095)	(0.026)	(0.044)	(0.099)	(0.097)	(0.032)	(0.012)	(0.126)	(0.094)	(0.104)
IMF Program	−1.663**	0.701**	−0.072	−0.079	0.833	−0.019	−0.157	5.004***	−1.130	−1.050
	(0.673)	(0.330)	(0.506)	(0.705)	(0.828)	(0.482)	(0.112)	(1.275)	(0.701)	(0.952)
UNSC Member	−1.022	0.713*	−0.547	0.997	−1.162	−0.129	0.052	3.084**	−1.059	0.702
	(0.984)	(0.376)	(0.687)	(0.907)	(1.220)	(0.956)	(0.128)	(1.183)	(0.832)	(1.145)
Voting with the US	1.598	−3.458	−2.898	10.562	8.737	−10.523***	−0.007	12.227	−0.174	−12.219***
	(4.150)	(2.533)	(3.636)	(6.692)	(5.726)	(2.251)	(1.355)	(7.466)	(3.626)	(3.949)
Intercept	4.923	7.264***	3.551	15.625**	9.981	11.208***	1.957*	4.984	−5.424	18.303***
	(4.509)	(2.305)	(2.938)	(5.535)	(5.979)	(3.194)	(1.125)	(6.488)	(5.385)	(4.594)
Observations	9680	9680	9680	9680	9680	9680	9680	9680	9680	9680
R^2	0.007	0.022	0.010	0.012	0.012	0.004	0.004	0.032	0.023	0.014

This table presents the results of ten linear regressions with standard errors clustered by country and year. The dependent variable is the prevalence of the corresponding topic, converted to a percentage. Other than *After 2019*, all independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

G Models for 2016–2022

The World Bank warns that the new taxonomy (which replaces "sectors" with "themes") is not comparable for the pre-2016 and post-2016 periods. Still, the main results are generally robust to excluding the pre-2016 period. As Table G.1 shows, relative to the period from January 2016 to December 2019, the number of projects with climate as the main theme significantly *decreased* after 2019, whereas the number of projects with climate as the secondary theme significantly *increased*.

Table G.1: Predictors of Project Sector and Theme, 2016–2022

	Dependent Variable:					
	Sector: Health	Theme: Health	Sector: Extractives	Sector: Renewables	Theme: Climate	Theme: Climate (Any)
	(1)	(2)	(3)	(4)	(5)	(6)
After 2019	1.150***	1.121***	−1.620***	−0.458***	−0.306**	1.093**
	(0.142)	(0.084)	(0.131)	(0.092)	(0.150)	(0.473)
Governance	−0.152	−0.178	−0.126	0.178	0.415**	0.369***
	(0.135)	(0.126)	(0.200)	(0.462)	(0.184)	(0.102)
Election Year	−0.204**	−0.157	0.347	0.050	−0.030	0.120
	(0.096)	(0.138)	(0.532)	(0.149)	(0.117)	(0.116)
EITI Member	−0.032	−0.126	0.612	−0.432	−0.185	0.119
	(0.091)	(0.088)	(0.660)	(0.390)	(0.176)	(0.129)
Field Discovery	−0.557*	−0.418*	0.099	−0.091	0.395*	0.175***
	(0.316)	(0.226)	(0.489)	(0.195)	(0.210)	(0.029)
SIDS	−0.024	−0.243**	0.331	0.506	0.311	0.419*
	(0.150)	(0.109)	(0.528)	(0.319)	(0.257)	(0.240)
Disaster	0.103	−0.130	−0.181	−0.128	0.381***	0.171*
	(0.178)	(0.206)	(0.335)	(0.171)	(0.129)	(0.092)
Log GDP per Capita	−0.061	0.028	0.343***	−0.220	0.287**	−0.043
	(0.071)	(0.098)	(0.106)	(0.173)	(0.120)	(0.091)
Log Resource Rents	0.019	0.012	0.412*	0.092	0.046	−0.035
	(0.041)	(0.057)	(0.225)	(0.085)	(0.054)	(0.030)
DAC Aid	−0.267***	−0.209***	0.253	0.134	0.008	0.026
	(0.052)	(0.055)	(0.325)	(0.189)	(0.070)	(0.073)
Chinese Finance	0.009*	0.008	−0.092*	0.013	−0.007	−0.024**
	(0.006)	(0.013)	(0.047)	(0.015)	(0.007)	(0.011)
IMF Program	0.009	−0.030	0.300	−0.294	−0.044	−0.044
	(0.119)	(0.087)	(0.508)	(0.191)	(0.143)	(0.122)
UNSC Member	0.124	−0.015	−0.106	0.173	0.534*	−0.179
	(0.156)	(0.114)	(0.394)	(0.156)	(0.325)	(0.211)
Voting with the US	−1.631***	−1.376*	0.033	1.168	−0.577	−1.681*
	(0.483)	(0.713)	(1.843)	(1.213)	(0.803)	(0.931)
Intercept	−1.676***	−2.264***	−7.610***	−1.669	−4.153***	0.932
	(0.487)	(0.672)	(0.820)	(1.554)	(0.921)	(0.909)
Observations	3168	3168	3168	3168	3168	3168
AIC	2382.8	2289.2	421.0	886.9	2235.4	3768.2

This table presents the results of six logistic regressions with standard errors clustered by country and year. The dependent variable indicates whether *Health*, *Extractives*, *Renewables*, or *Climate* is the project's main sector or theme, except for Model 6, whose dependent variable indicates whether *Climate* is either the project's main or its secondary theme. Other than *After 2019*, all independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

H Other Cut-Offs

As a placebo test, we replace *After 2019* with *After 2017* (Table H.1), *After 2018* (Table H.2), and *After 2020* (Table H.3). These models suggest that the significant decline in extractive projects began before 2019, though the magnitude of the effect increased over time. This suggests that 2019 did not represent a distinct structural break in World Bank lending patterns; the Bank simply continued to follow existing trends.

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

	Dependent Variable:					
	Sector: Health	Theme: Health	Sector: Extractives	Sector: Renewables	Theme: Climate	Theme: Climate (Any)
	(1)	(2)	(3)	(4)	(5)	(6)
After 2017 (Placebo)	0.974***	0.790***	−1.158***	−0.278**	0.498***	2.804***
	(0.206)	(0.201)	(0.402)	(0.124)	(0.188)	(0.306)
Governance	−0.170*	−0.122*	−0.281	0.241	0.351***	0.291**
	(0.092)	(0.072)	(0.214)	(0.196)	(0.133)	(0.115)
Election Year	−0.007	−0.008	0.248	−0.083	−0.060	0.047
	(0.094)	(0.076)	(0.210)	(0.149)	(0.082)	(0.080)
EITI Member	−0.015	−0.128	1.302***	−0.192	−0.027	0.314
	(0.070)	(0.086)	(0.227)	(0.255)	(0.166)	(0.214)
Field Discovery	−0.294*	−0.101	−0.069	−0.194	0.441***	0.348*
	(0.155)	(0.179)	(0.326)	(0.248)	(0.169)	(0.189)
SIDS	0.030	−0.187***	0.802***	0.141	0.186	0.114
	(0.124)	(0.040)	(0.302)	(0.239)	(0.219)	(0.181)
Disaster	0.007	−0.099	0.018	−0.024	0.210**	0.005
	(0.091)	(0.089)	(0.168)	(0.124)	(0.107)	(0.081)
Log GDP per Capita	−0.085	0.106*	0.168*	−0.058	0.311***	0.044
	(0.060)	(0.057)	(0.098)	(0.108)	(0.098)	(0.095)
Log Resource Rents	0.038	0.036	0.265**	−0.002	0.018	−0.011
	(0.023)	(0.025)	(0.116)	(0.050)	(0.034)	(0.032)
DAC Aid	−0.103	0.005	0.033	0.072***	0.037	0.040
	(0.065)	(0.034)	(0.034)	(0.018)	(0.043)	(0.050)
Chinese Finance	0.006	0.001	−0.041	−0.006	−0.003	0.004
	(0.005)	(0.010)	(0.027)	(0.013)	(0.013)	(0.015)
IMF Program	0.039	0.008	0.299	−0.095	−0.288***	−0.391***
	(0.063)	(0.065)	(0.183)	(0.140)	(0.106)	(0.105)
UNSC Member	0.138	−0.046	0.047	0.260**	0.041	−0.072
	(0.114)	(0.093)	(0.220)	(0.130)	(0.190)	(0.155)
Voting with the US	−0.948**	−0.806*	0.087	−1.314	−0.027	1.784
	(0.385)	(0.486)	(1.480)	(1.064)	(0.785)	(1.241)
Intercept	−1.868***	−3.135***	−6.468***	−2.410***	−4.922***	−2.099***
	(0.470)	(0.458)	(0.896)	(0.884)	(0.754)	(0.727)
Observations	9680	9680	9680	9680	9680	9680
AIC	5766.3	5977.2	1513.5	2965.2	5477.3	8927.0

This table presents the results of six logistic regressions with standard errors clustered by country and year. The dependent variable indicates whether *Health*, *Extractives*, *Renewables*, or *Climate* is the project's main sector or theme, except for Model 6, whose dependent variable indicates whether *Climate* is either the project's main or its secondary theme. Other than *After 2017*, all independent variables are lagged at $t-1$. $^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$

Table H.2: Predictors of Project Sector and Theme, 2001–2022

	Dependent Variable:					
	Sector: Health	Theme: Health	Sector: Extractives	Sector: Renewables	Theme: Climate	Theme: Climate (Any)
	(1)	(2)	(3)	(4)	(5)	(6)
After 2018 (Placebo)	1.094***	0.918***	−1.490***	−0.335***	0.415**	2.714***
	(0.183)	(0.173)	(0.318)	(0.124)	(0.198)	(0.340)
Governance	−0.175*	−0.124	−0.276	0.242	0.338**	0.220*
	(0.094)	(0.076)	(0.212)	(0.197)	(0.137)	(0.129)
Election Year	−0.034	−0.030	0.281	−0.078	−0.070	−0.032
	(0.094)	(0.074)	(0.208)	(0.150)	(0.086)	(0.112)
EITI Member	−0.013	−0.138	1.299***	−0.192	0.019	0.489**
	(0.069)	(0.086)	(0.225)	(0.252)	(0.159)	(0.231)
Field Discovery	−0.304**	−0.101	−0.041	−0.194	0.425**	0.251
	(0.148)	(0.184)	(0.321)	(0.248)	(0.168)	(0.202)
SIDS	0.041	−0.182***	0.803***	0.138	0.206	0.204
	(0.127)	(0.047)	(0.307)	(0.240)	(0.219)	(0.157)
Disaster	0.002	−0.103	0.025	−0.023	0.217**	0.032
	(0.092)	(0.089)	(0.172)	(0.124)	(0.106)	(0.089)
Log GDP per Capita	−0.088	0.103*	0.171*	−0.057	0.315***	0.060
	(0.059)	(0.058)	(0.098)	(0.108)	(0.099)	(0.095)
Log Resource Rents	0.039	0.037	0.269**	−0.002	0.011	−0.035
	(0.025)	(0.026)	(0.116)	(0.050)	(0.034)	(0.040)
DAC Aid	−0.099	0.006	0.033	0.072***	0.039	0.049
	(0.063)	(0.033)	(0.033)	(0.019)	(0.044)	(0.052)
Chinese Finance	0.010*	0.004	−0.048*	−0.007	−0.003	0.010
	(0.005)	(0.010)	(0.027)	(0.013)	(0.013)	(0.016)
IMF Program	0.043	0.012	0.293*	−0.095	−0.300***	−0.400***
	(0.063)	(0.067)	(0.177)	(0.139)	(0.110)	(0.098)
UNSC Member	0.140	−0.046	0.033	0.261**	0.030	−0.092
	(0.108)	(0.092)	(0.222)	(0.129)	(0.192)	(0.155)
Voting with the US	−0.975**	−0.831*	0.163	−1.313	0.007	1.731
	(0.394)	(0.498)	(1.484)	(1.062)	(0.761)	(1.133)
Intercept	−1.839***	−3.107***	−6.533***	−2.417***	−4.921***	−2.075***
	(0.468)	(0.462)	(0.896)	(0.883)	(0.757)	(0.715)
Observations	9680	9680	9680	9680	9680	9680
AIC	5739.1	5952.2	1507.1	2964.4	5489.7	9329.1

This table presents the results of six logistic regressions with standard errors clustered by country and year. The dependent variable indicates whether *Health*, *Extractives*, *Renewables*, or *Climate* is the project's main sector or theme, except for Model 6, whose dependent variable indicates whether *Climate* is either the project's main or its secondary theme. Other than *After 2018*, all independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table H.3: Predictors of Project Sector and Theme, 2001–2022

	Dependent Variable:					
	Sector: Health	Theme: Health	Sector: Extractives	Sector: Renewables	Theme: Climate	Theme: Climate (Any)
	(1)	(2)	(3)	(4)	(5)	(6)
After 2020 (Placebo)	0.925***	0.880***	−1.675***	−0.386***	0.305**	2.660***
	(0.202)	(0.160)	(0.273)	(0.065)	(0.151)	(0.366)
Governance	−0.214**	−0.150**	−0.259	0.248	0.325**	0.115
	(0.085)	(0.067)	(0.218)	(0.194)	(0.139)	(0.146)
Election Year	−0.018	−0.014	0.265	−0.082	−0.061	0.026
	(0.089)	(0.071)	(0.199)	(0.149)	(0.083)	(0.078)
EITI Member	0.142	−0.033	1.157***	−0.221	0.091	0.784***
	(0.149)	(0.108)	(0.228)	(0.256)	(0.145)	(0.254)
Field Discovery	−0.331**	−0.122	−0.059	−0.188	0.409**	0.137
	(0.144)	(0.183)	(0.326)	(0.250)	(0.169)	(0.187)
SIDS	0.080	−0.155**	0.730**	0.131	0.227	0.267**
	(0.143)	(0.063)	(0.291)	(0.236)	(0.213)	(0.132)
Disaster	0.014	−0.093	0.032	−0.026	0.227**	0.073
	(0.089)	(0.084)	(0.170)	(0.124)	(0.107)	(0.105)
Log GDP per Capita	−0.065	0.118**	0.156	−0.061	0.322***	0.108
	(0.063)	(0.058)	(0.100)	(0.108)	(0.099)	(0.096)
Log Resource Rents	0.008	0.015	0.309**	0.003	0.000	−0.098*
	(0.033)	(0.024)	(0.121)	(0.049)	(0.034)	(0.054)
DAC Aid	−0.101*	0.003	0.035	0.072***	0.040	0.039
	(0.057)	(0.033)	(0.034)	(0.019)	(0.045)	(0.062)
Chinese Finance	0.009*	0.005	−0.048*	−0.007	−0.003	0.009
	(0.005)	(0.009)	(0.029)	(0.013)	(0.013)	(0.019)
IMF Program	0.009	−0.012	0.304*	−0.088	−0.316***	−0.431***
	(0.065)	(0.066)	(0.180)	(0.139)	(0.111)	(0.099)
UNSC Member	0.076	−0.102	0.043	0.277**	0.014	−0.239
	(0.122)	(0.098)	(0.213)	(0.130)	(0.188)	(0.156)
Voting with the US	−1.023***	−0.905*	0.524	−1.293	0.011	1.277
	(0.376)	(0.550)	(1.446)	(1.068)	(0.744)	(1.099)
Intercept	−1.850***	−3.098***	−6.576***	−2.413***	−4.932***	−2.089***
	(0.459)	(0.471)	(0.922)	(0.881)	(0.753)	(0.712)
Observations	9680	9680	9680	9680	9680	9680
AIC	5833.2	6002.6	1518.2	2965.7	5503.5	10 310.9

This table presents the results of six logistic regressions with standard errors clustered by country and year. The dependent variable indicates whether *Health*, *Extractives*, *Renewables*, or *Climate* is the project's main sector or theme, except for Model 6, whose dependent variable indicates whether *Climate* is either the project's main or its secondary theme. Other than *After 2020*, all independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

I Models With Country-Year Data

The main models use a World Bank project as the unit of analysis. Yet it is also possible to aggregate the data by country and year, shifting the focus from individual projects to country-level patterns to understand policy shifts over time. These two analyses are not directly comparable, as they capture distinct aspects of the data and answer different research questions, but they might be useful in understanding how the dynamics of World Bank lending change over time.

Table I.1 presents the results of six Poisson models; in each model, the outcome is the *count* of projects belonging to the corresponding sector or theme. The number of projects belonging to *Sector: Extractives* and *Sector: Renewables* declined significantly after 2019, whereas the number of projects belonging to the climate theme — however this theme is measured — increased significantly.

Table I.1: Predictors of Project Sector and Theme Over Time, 2001–2022

	Dependent Variable:					
	Count, Sector: Health	Count, Theme: Health	Count, Sector: Extractives	Count, Sector: Renewables	Count, Theme: Climate	Count, Theme: Climate (Any)
	(1)	(2)	(3)	(4)	(5)	(6)
After 2019	1.280***	1.131***	−1.593***	−0.185*	0.430***	1.424***
	(0.118)	(0.099)	(0.199)	(0.099)	(0.159)	(0.220)
Governance	−0.015	−0.046	−0.181	0.182	0.053	0.020
	(0.115)	(0.114)	(0.205)	(0.192)	(0.184)	(0.144)
Election Year	−0.135*	−0.138	0.137	−0.195	−0.178	−0.100
	(0.070)	(0.094)	(0.185)	(0.145)	(0.122)	(0.074)
EITI Member	0.240**	0.115	1.721***	0.104	0.222	0.519***
	(0.105)	(0.124)	(0.269)	(0.282)	(0.188)	(0.161)
Field Discovery	0.238	0.491*	0.382	0.456	0.996***	0.611***
	(0.190)	(0.283)	(0.258)	(0.304)	(0.284)	(0.234)
SIDS	−0.420***	−0.626***	0.116	−0.397	−0.190	−0.244*
	(0.157)	(0.140)	(0.269)	(0.287)	(0.266)	(0.135)
Disaster	0.305***	0.271**	0.309*	0.349**	0.623***	0.325***
	(0.100)	(0.118)	(0.171)	(0.152)	(0.169)	(0.109)
Log GDP per Capita	−0.496***	−0.373***	−0.248***	−0.481***	−0.226	−0.456***
	(0.069)	(0.093)	(0.088)	(0.137)	(0.147)	(0.106)
Log Resource Rents	−0.048*	−0.060**	0.118	−0.078	−0.078**	−0.103***
	(0.025)	(0.026)	(0.104)	(0.050)	(0.038)	(0.031)
DAC Aid	0.090***	0.114***	0.117***	0.147***	0.127***	0.135***
	(0.026)	(0.020)	(0.030)	(0.024)	(0.042)	(0.043)
Chinese Finance	0.038***	0.035***	−0.015	0.025**	0.029**	0.040***
	(0.005)	(0.010)	(0.021)	(0.012)	(0.014)	(0.012)
IMF Program	0.090	0.078	0.299*	−0.032	−0.182	−0.183*
	(0.084)	(0.114)	(0.167)	(0.174)	(0.155)	(0.103)
UNSC Member	0.321**	0.189	0.248	0.556***	0.302	0.118
	(0.128)	(0.142)	(0.231)	(0.173)	(0.226)	(0.152)
Voting with the US	−2.155***	−2.341***	−0.666	−2.795**	−2.316**	−0.848
	(0.510)	(0.704)	(1.127)	(1.366)	(1.163)	(0.808)
Intercept	2.265***	1.499**	−2.298***	1.730	0.142	2.894***
	(0.606)	(0.761)	(0.825)	(1.107)	(1.160)	(0.858)
Observations	3868	3868	3868	3868	3868	3868
AIC	3787.9	4074.2	1108.9	2216.3	4305.8	8966.3

This table presents the results of six Poisson regressions with standard errors clustered by country and year. For every country and year, the dependent variable indicates the number of projects with *Health*, *Extractives*, *Renewables*, or *Climate* as the main sector or theme, except for Model 6, whose dependent variable indicates the number of projects with *Climate* as either the main or secondary theme. Other than *After 2019*, all independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Turning to the total commitments, Tables I.2 and I.3 present the results of linear regressions whose dependent variables represent the total commitments to each sector or theme (in log USD or percentage of total commitments, respectively). From a country-level perspective, the World Bank has committed significantly fewer resources to extractive initiatives after 2019, both in absolute and relative terms. Considerably more resources are going into climate projects in the aggregate — even if each climate project is not significantly larger than before, as the main analysis shows.

Table I.2: Predictors of Project Commitments (in Log USD), 2001–2022

	Dependent Variable:					
	Log USD, Sector: Health	Log USD, Theme: Health	Log USD, Sector: Extractives	Log USD, Sector: Renewables	Log USD, Theme: Climate	Log USD, Theme: Climate (Any)
	(1)	(2)	(3)	(4)	(5)	(6)
After 2019	4.731***	4.269***	−0.595***	0.005	1.644***	6.912***
	(0.832)	(0.632)	(0.142)	(0.119)	(0.404)	(0.711)
Governance	0.427	0.058	0.008	0.278	0.311	0.244
	(0.268)	(0.273)	(0.107)	(0.258)	(0.320)	(0.480)
Election Year	−0.350*	−0.294	−0.031	−0.205	−0.211	−0.087
	(0.198)	(0.197)	(0.110)	(0.157)	(0.200)	(0.282)
EITI Member	1.023*	0.767	1.493***	−0.174	1.018	3.850***
	(0.570)	(0.499)	(0.398)	(0.412)	(0.596)	(1.030)
Field Discovery	0.331	0.748	0.198	0.384	1.894**	1.832*
	(0.575)	(0.712)	(0.183)	(0.322)	(0.794)	(0.951)
SIDS	−1.383***	−1.554***	0.013	−0.343	−0.174	−0.062
	(0.290)	(0.231)	(0.088)	(0.221)	(0.472)	(0.558)
Disaster	0.661***	0.449*	0.107	0.194	0.811**	0.651
	(0.197)	(0.218)	(0.077)	(0.120)	(0.298)	(0.412)
Log GDP per Capita	−1.392***	−1.022***	−0.097	−0.552***	−0.658**	−1.787***
	(0.248)	(0.268)	(0.058)	(0.159)	(0.257)	(0.442)
Log Resource Rents	−0.121**	−0.159***	0.026	−0.055	−0.148*	−0.292**
	(0.054)	(0.047)	(0.019)	(0.050)	(0.072)	(0.110)
DAC Aid	0.900**	1.287***	0.316***	0.719***	0.693	0.882
	(0.397)	(0.330)	(0.108)	(0.164)	(0.478)	(0.629)
Chinese Finance	0.191**	0.158**	−0.010	0.036	0.180**	0.258**
	(0.073)	(0.070)	(0.013)	(0.024)	(0.082)	(0.111)
IMF Program	0.755**	0.625	0.152	−0.186	−0.263	−0.164
	(0.347)	(0.387)	(0.139)	(0.230)	(0.315)	(0.474)
UNSC Member	0.919*	0.354	0.064	0.482	0.892	0.731
	(0.523)	(0.461)	(0.132)	(0.297)	(0.525)	(0.534)
Voting with the US	−3.271***	−3.452***	−0.091	−1.179	−2.661*	−1.477
	(1.022)	(0.928)	(0.286)	(0.745)	(1.347)	(2.082)
Intercept	14.270***	11.345***	1.013*	5.932***	7.498***	18.636***
	(2.311)	(2.465)	(0.498)	(1.445)	(2.354)	(4.179)
Observations	3868	3868	3868	3868	3868	3868
R^2	0.034	0.030	0.014	0.009	0.012	0.038

This table presents the results of six linear regressions with standard errors clustered by country and year. For every country and year, the dependent variable indicates the total amount of IDA/IBRD commitments to projects in the corresponding sector or theme, in logged billions of 2023 USD. Other than *After 2019*, all independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table I.3: Predictors of Project Commitments (Percentage of Total IDA/IBRD Commitments), 2001–2022

	Dependent Variable:					
	% Total, Sector: Health	% Total, Theme: Health	% Total, Sector: Extractives	% Total, Sector: Renewables	% Total, Theme: Climate	% Total, Theme: Climate (Any)
	(1)	(2)	(3)	(4)	(5)	(6)
After 2019	11.217***	9.656***	−0.870*	−0.180	3.978***	59.794***
	(1.608)	(1.197)	(0.497)	(0.395)	(1.382)	(6.817)
Governance	−2.670**	−2.430*	−0.824**	0.031	2.739*	3.021
	(1.214)	(1.202)	(0.393)	(0.644)	(1.320)	(2.275)
Election Year	−0.696	−0.274	−0.339	−0.107	0.641	1.058
	(1.169)	(0.979)	(0.375)	(0.656)	(0.959)	(2.183)
EITI Member	−0.161	−1.398	1.208*	−0.556	0.376	14.122***
	(1.236)	(1.292)	(0.652)	(0.868)	(0.885)	(4.889)
Field Discovery	−5.342***	−2.994*	0.448	−0.103	3.178*	1.968
	(1.260)	(1.721)	(0.812)	(0.853)	(1.703)	(2.899)
SIDS	−0.925	−2.841**	1.236*	1.050	2.956	6.075*
	(1.329)	(1.211)	(0.690)	(0.944)	(2.090)	(3.226)
Disaster	0.439	−0.936	−0.217	−0.654	2.522**	0.531
	(1.141)	(1.073)	(0.370)	(0.566)	(1.145)	(1.840)
Log GDP per Capita	−0.118	0.563	0.725**	−0.066	2.224***	0.049
	(0.639)	(0.596)	(0.329)	(0.279)	(0.738)	(1.339)
Log Resource Rents	0.119	−0.200	0.302*	−0.007	−0.031	−1.259
	(0.367)	(0.379)	(0.151)	(0.149)	(0.282)	(0.774)
DAC Aid	−0.793**	−0.254	0.027	0.884***	0.164	0.942
	(0.369)	(0.337)	(0.102)	(0.279)	(0.281)	(0.890)
Chinese Finance	0.039	0.099	−0.088***	−0.036	0.136	0.582
	(0.097)	(0.077)	(0.028)	(0.050)	(0.155)	(0.463)
IMF Program	0.484	−0.533	0.396	−0.529	−1.800*	−6.342***
	(0.837)	(0.727)	(0.358)	(0.545)	(0.957)	(1.899)
UNSC Member	2.468	−0.236	−0.753***	0.757	0.782	−4.384*
	(1.756)	(1.394)	(0.220)	(1.233)	(1.926)	(2.545)
Voting with the US	−15.324***	−9.360**	1.571	−1.320	3.067	21.693
	(3.590)	(4.069)	(2.609)	(2.996)	(5.686)	(16.568)
Intercept	10.706**	6.190	−5.823**	3.663*	−12.275**	17.892
	(4.400)	(4.238)	(2.694)	(1.928)	(5.778)	(10.669)
Observations	2321	2321	2321	2321	2321	2321
R^2	0.006	0.004	0.003	0.001	0.006	0.042

This table presents the results of six linear regressions with standard errors clustered by country and year. For every country and year, the dependent variable indicates the total amount of IDA/IBRD commitments to projects in the corresponding sector or theme, as a percentage of total IDA/IBRD commitments. Other than *After 2019*, all independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

J Models With Country Fixed Effects

Tables J.1, J.2, J.3, and J.4 reproduce the main models, including country fixed effects. These alternative models exclude the dichotomous indicator *SIDS*, which is perfectly collinear with the country fixed effects. Other than that, the results are nearly identical to the main ones.

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

	Dependent Variable:					
	Sector: Health	Theme: Health	Sector: Extractives	Sector: Renewables	Theme: Climate	Theme: Climate (Any)
	(1)	(2)	(3)	(4)	(5)	(6)
After 2019	1.193***	1.179***	−1.948***	−0.509***	−0.053	1.989***
	(0.114)	(0.081)	(0.284)	(0.128)	(0.171)	(0.479)
Governance	−0.135	−0.382	0.083	0.473	−0.241	−0.491
	(0.308)	(0.295)	(0.652)	(0.478)	(0.393)	(0.449)
Election Year	−0.103	−0.076	0.114	−0.021	0.049	0.122
	(0.093)	(0.072)	(0.214)	(0.167)	(0.073)	(0.087)
EITI Member	0.030	−0.155	0.213	−0.129	0.199	0.679***
	(0.137)	(0.166)	(0.271)	(0.244)	(0.212)	(0.263)
Field Discovery	−0.015	0.046	0.282	−0.342	0.115	−0.258***
	(0.182)	(0.184)	(0.279)	(0.327)	(0.141)	(0.091)
Disaster	0.062	−0.018	0.112	−0.185	−0.012	−0.109
	(0.085)	(0.087)	(0.213)	(0.191)	(0.150)	(0.141)
Log GDP per Capita	−0.134	−0.100	1.647**	0.121	1.733***	3.326***
	(0.265)	(0.185)	(0.837)	(0.428)	(0.448)	(1.007)
Log Resource Rents	−0.172***	−0.044	0.210	0.020	0.168	−0.141
	(0.063)	(0.073)	(0.191)	(0.105)	(0.128)	(0.149)
DAC Aid	−0.004	0.062***	−0.002	0.111**	0.031	0.051
	(0.040)	(0.024)	(0.025)	(0.046)	(0.085)	(0.059)
Chinese Finance	0.005	0.012	−0.072**	−0.008	0.004	0.008
	(0.007)	(0.009)	(0.036)	(0.014)	(0.012)	(0.017)
IMF Program	0.001	−0.007	0.049	0.007	0.110	−0.029
	(0.081)	(0.090)	(0.189)	(0.177)	(0.102)	(0.112)
UNSC Member	0.173**	0.026	−0.046	0.313**	0.042	−0.166
	(0.069)	(0.055)	(0.188)	(0.123)	(0.210)	(0.148)
Voting with the US	−1.805***	−2.726***	0.131	−2.461	1.535	3.595*
	(0.595)	(0.823)	(1.828)	(1.613)	(0.993)	(1.873)
Observations	9545	9549	5249	8539	9340	9604
AIC	5777.7	5985.4	1434.1	2944.3	5361.9	9096.2

This table presents the results of six logistic regressions with country fixed effects and standard errors clustered by country and year. The dependent variable indicates whether *Health*, *Extractives*, *Renewables*, or *Climate* is the project's main sector or theme, except for Model 6, whose dependent variable indicates whether *Climate* is either the project's main or its secondary theme. Other than *After 2019*, all independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table J.2: Predictors of Topic Proportions, 2001–2022

	Dependent Variable:			
	Topic: Health (%)	Topic: Extractives (%)	Topic: Renewables (%)	Topic: Climate (%)
	(1)	(2)	(3)	(4)
After 2019	0.178***	−0.017***	−0.027***	−0.003
	(0.014)	(0.004)	(0.006)	(0.007)
Governance	−0.082***	0.008	0.021	−0.021
	(0.029)	(0.009)	(0.013)	(0.016)
Election Year	−0.010**	0.005**	0.003	0.000
	(0.004)	(0.002)	(0.006)	(0.005)
EITI Member	0.012	−0.001	0.011	−0.001
	(0.008)	(0.004)	(0.008)	(0.007)
Field Discovery	0.005	−0.003	−0.008	0.003
	(0.010)	(0.005)	(0.009)	(0.006)
Disaster	0.009	0.007**	−0.012*	−0.005
	(0.008)	(0.003)	(0.007)	(0.006)
Log GDP per Capita	0.019	−0.013*	0.003	0.068***
	(0.022)	(0.007)	(0.011)	(0.016)
Log Resource Rents	−0.019**	0.006**	0.005	0.010**
	(0.008)	(0.003)	(0.004)	(0.004)
DAC Aid	0.006*	0.002	0.001	0.000
	(0.003)	(0.001)	(0.002)	(0.002)
Chinese Finance	0.001	0.000	0.001	0.000
	(0.001)	(0.000)	(0.001)	(0.001)
IMF Program	0.002	0.000	0.003	−0.007
	(0.006)	(0.003)	(0.005)	(0.005)
UNSC Member	0.005	−0.001	−0.011	0.001
	(0.007)	(0.004)	(0.007)	(0.009)
Voting with the US	−0.089*	−0.032*	−0.078**	0.068*
	(0.047)	(0.018)	(0.031)	(0.035)
Observations	9680	9680	9680	9680
R^2	0.117	0.051	0.043	0.078

This table presents the results of four linear regressions with country fixed effects and standard errors clustered by country and year. The dependent variable is the prevalence of the corresponding topic, converted to a percentage. Other than *After 2019*, all independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table J.3: Predictors of Project Commitments, 2001–2022

	Dependent Variable:					
	Log USD	% Total	Log USD	% Total	Log USD	% Total
	(1)	(2)	(3)	(4)	(5)	(6)
After 2019	0.626***	−0.015	0.689***	−0.014	−0.380	0.011
	(0.151)	(0.019)	(0.160)	(0.019)	(0.255)	(0.100)
Sector: Extractives	−3.451***	−0.135***				
	(0.535)	(0.039)				
Sector: Extractives × After 2019	2.559	0.451				
	(1.855)	(0.297)				
Sector: Renewables	−1.896***	−0.005				
	(0.419)	(0.056)				
Sector: Renewables × After 2019	1.660***	−0.006				
	(0.489)	(0.067)				
Theme: Climate			−1.219***	−0.095***		
			(0.303)	(0.033)		
Theme: Climate × After 2019			0.812*	0.038		
			(0.401)	(0.030)		
Theme: Climate (Any)					0.078	0.021
					(0.286)	(0.032)
Theme: Climate (Any) × After 2019					1.406***	−0.037
					(0.371)	(0.116)
Governance	0.178	0.111*	0.114	0.109*	0.166	0.115*
	(0.269)	(0.057)	(0.288)	(0.057)	(0.281)	(0.057)
Election Year	0.006	−0.004	0.002	−0.003	−0.012	−0.004
	(0.056)	(0.012)	(0.058)	(0.012)	(0.060)	(0.012)
EITI Member	0.062	0.032	0.036	0.032	0.025	0.030
	(0.151)	(0.024)	(0.166)	(0.023)	(0.150)	(0.023)
Field Discovery	−0.005	−0.005	0.010	−0.005	0.018	−0.005
	(0.079)	(0.019)	(0.081)	(0.018)	(0.084)	(0.019)
Disaster	0.033	0.001	0.032	0.001	0.048	0.001
	(0.081)	(0.017)	(0.086)	(0.017)	(0.086)	(0.017)
Log GDP per Capita	0.441*	−0.099*	0.545*	−0.089	0.360	−0.113**
	(0.235)	(0.056)	(0.282)	(0.055)	(0.249)	(0.053)
Log Resource Rents	−0.224***	−0.011	−0.223***	−0.010	−0.230***	−0.010
	(0.069)	(0.019)	(0.074)	(0.019)	(0.067)	(0.019)
DAC Aid	0.007	−0.013**	−0.004	−0.013**	−0.010	−0.013**
	(0.032)	(0.006)	(0.035)	(0.006)	(0.034)	(0.006)
Chinese Finance	0.003	−0.001	0.006	−0.001	0.006	−0.001
	(0.005)	(0.002)	(0.006)	(0.001)	(0.005)	(0.002)
IMF Program	−0.088	0.016	−0.082	0.016	−0.085	0.016
	(0.086)	(0.018)	(0.084)	(0.018)	(0.082)	(0.018)
UNSC Member	−0.026	−0.001	−0.054	−0.001	−0.044	−0.001
	(0.081)	(0.021)	(0.079)	(0.021)	(0.080)	(0.020)
Voting with the US	0.878	0.329*	1.126	0.337*	0.867	0.314
	(0.704)	(0.181)	(0.678)	(0.179)	(0.704)	(0.188)
Observations	9680	9680	9680	9680	9680	9680
R^2	0.152	0.107	0.127	0.107	0.121	0.106

This table presents the results of six linear regressions with country fixed effects and standard errors clustered by country and year. The dependent variable indicates the total amount of IDA/IBRD commitments to each project, in logged billions of 2023 USD (Models 1, 3, and 5) or as a percentage of total IDA/IBRD commitments (Models 2, 4, and 6). Other than *After 2019* and the sectors or themes, all independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table J.4: Predictors of Project End, 2001–2022

	Dependent Variable:		
	Probability of End	Probability of End	Probability of End
	(1)	(2)	(3)
After 2019	−0.203***	−0.257***	−0.162**
	(0.061)	(0.062)	(0.072)
Sector: Extractives	0.576***		
	(0.141)		
Sector: Extractives × After 2019	0.497**		
	(0.217)		
Sector: Renewables	−0.607***		
	(0.119)		
Sector: Renewables × After 2019	−0.212		
	(0.256)		
Theme: Climate		−0.650***	
		(0.075)	
Theme: Climate × After 2019		0.593***	
		(0.118)	
Theme: Climate (Any)			−0.696***
			(0.056)
Theme: Climate (Any) × After 2019			0.287***
			(0.092)
Governance	−0.038	−0.077	−0.148
	(0.167)	(0.167)	(0.170)
Election Year	0.046	0.046	0.039
	(0.034)	(0.034)	(0.034)
EITI Member	0.148*	0.158*	0.178**
	(0.089)	(0.089)	(0.090)
Field Discovery	0.123*	0.128*	0.118*
	(0.071)	(0.070)	(0.070)
Disaster	−0.026	−0.030	−0.034
	(0.038)	(0.038)	(0.038)
Log GDP per Capita	0.122	0.192	0.347**
	(0.126)	(0.130)	(0.137)
Log Resource Rents	−0.033	−0.030	−0.036
	(0.050)	(0.051)	(0.052)
DAC Aid	−0.063*	−0.065*	−0.060
	(0.035)	(0.036)	(0.037)
Chinese Finance	−0.005	−0.005	−0.005
	(0.004)	(0.004)	(0.005)
IMF Program	0.072	0.074	0.068
	(0.051)	(0.050)	(0.052)
UNSC Member	−0.006	−0.011	−0.018
	(0.058)	(0.057)	(0.058)
Voting with the US	1.484***	1.570***	1.702***
	(0.380)	(0.376)	(0.374)
Observations	49 099	49 099	48 999
AIC	36 542.9	36 534.0	36 264.3

This table presents the results of three logistic regressions with country fixed effects, standard errors clustered by country, and duration-dependent dummy variables. The dependent variable indicates the probability of a project ending at a given point, conditional on not having ended previously. Other than *After 2019* and the sectors or themes, all independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

K Cox Proportional Hazard Models

Following Beck, Katz and Tucker (1998), the main analysis presents the results of logistic regressions with duration-dependent dummies. Table K.1 presents the results of three Cox proportional hazard models, which are conceptually similar but less straightforward to interpret.

Table K.1: Predictors of Project End, 2001–2022

	Dependent Variable:		
	Probability of End	Probability of End	Probability of End
	(1)	(2)	(3)
After 2019	−0.133***	−0.174***	−0.079*
	(0.033)	(0.035)	(0.041)
Sector: Extractives	0.427***		
	(0.096)		
Sector: Extractives × After 2019	0.437*		
	(0.228)		
Sector: Renewables	−0.499***		
	(0.074)		
Sector: Renewables × After 2019	−0.199		
	(0.195)		
Theme: Climate		−0.536***	
		(0.054)	
Theme: Climate × After 2019		0.496***	
		(0.104)	
Theme: Climate (Any)			−0.567***
			(0.040)
Theme: Climate (Any) × After 2019			0.230***
			(0.072)
Governance	0.026	0.030	0.044
	(0.031)	(0.031)	(0.031)
Election Year	0.036	0.034	0.024
	(0.027)	(0.027)	(0.027)
EITI Member	0.104***	0.124***	0.140***
	(0.030)	(0.029)	(0.029)
Field Discovery	0.136***	0.151***	0.157***
	(0.035)	(0.035)	(0.035)
SIDS	0.146***	0.144***	0.157***
	(0.048)	(0.048)	(0.048)
Disaster	−0.054*	−0.051	−0.050
	(0.031)	(0.031)	(0.032)
Log GDP per Capita	−0.052***	−0.040**	−0.042**
	(0.018)	(0.018)	(0.018)
Log Resource Rents	−0.023**	−0.022**	−0.024***
	(0.009)	(0.009)	(0.009)
DAC Aid	−0.057***	−0.058***	−0.055***
	(0.016)	(0.016)	(0.016)
Chinese Finance	−0.006**	−0.007**	−0.007**
	(0.003)	(0.003)	(0.003)
IMF Program	0.063**	0.057**	0.042
	(0.027)	(0.027)	(0.027)
UNSC Member	−0.012	−0.013	−0.021
	(0.046)	(0.046)	(0.046)
Voting with the US	0.378**	0.399***	0.480***
	(0.148)	(0.147)	(0.146)
Observations	49 109	49 109	49 009
AIC	114 173.6	114 161.0	113 632.2

This table presents the results of three Cox proportional hazard regressions with time-varying covariates. The dependent variable indicates the instantaneous risk of a project ending at a given point, conditional on not having ended previously. Other than *After 2019* and the sectors or themes, all independent variables are lagged at $t-1$. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

References

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