Pledge and Prejudice: The Reality of International Climate Commitments

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Abstract

What prompts international organizations to violate their climate commitments? In 2017, the World Bank pledged to stop funding upstream oil and gas projects after 2019. However, high-profile instances of continued funding — in Guyana, Indonesia, and elsewhere — have cast doubt on this pledge. This study uses text analysis and statistics to examine the content of all World Bank projects approved between 2001 and 2022. Results identify a significant reduction in extractive project funding in favor of climate projects since 2019, although this shift appears to be part of a gradual, decade-long trend rather than a direct consequence of an official policy change. This study provides insights into the trade-offs faced by international actors in balancing developmental and environmental goals, highlighting the World Bank's slow but growing role in global climate finance.

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1 Introduction

In 2016, the World Bank Group released its first Climate Change Action Plan. Recognizing that climate change posed a threat to its core mission of ending poverty and boosting prosperity, the entity 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, the World Bank Group announced in 2017 that it would no longer finance upstream oil and gas projects by 2019. In 2021, its two private sector units — 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" and helping countries reach their Nationally Determined Contributions and Long-Term Strategies (World Bank Group, 2021, 15).

There is widespread evidence that the Bank met the first part of its promise: at COP28 in 2023, it announced 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.[1] As of 2023, it is the single largest provider of multilateral climate finance to low- and middle-income countries (European Investment Bank, 2024). The Bank has been far less transparent about its success in meeting the second part of the promise. Indeed, environmental groups have decried various instances where the institution violated its own pledges. Guyana received $55 million to train oil and gas officials and revamp the banking and insurance sectors in 2020,[2] and the IFC indirectly backed the construction of two Indonesian coal-fired power plants in 2023.[3] Granted, these financing decisions do not directly contradict the World

[1] https://www.worldbank.org/en/news/press-release/2023/12/01/world-bank-group-doubles-down-on-financial-ambition-to-drive-climate-action-and-build-resilience

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

[3] David Stanway and Fransiska Nangoy. 2023. "Green Groups Slam World Bank for Backing Indonesian

Bank's promises, as they do not involve *upstream* oil and gas projects or *new* coal-fired power plants.[4] Yet they are unsurprising for another reason: even as the organization committed to divesting from fossil fuels, it noted that "in exceptional circumstances" and "in the poorest countries," it would continue to support initiatives that increased energy access.[5] This study answers a descriptive question: has the World Bank reduced oil and gas funding after 2019? What "exceptional circumstances," if any, have prompted the World Bank to violate its climate commitments?

I answer this question using data on all projects funded by two organizations of the World Bank Group: 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.[6] Topic models provide descriptive information about the content of World Bank projects over time and linear regressions help identify the predictors of variation in topic proportions. As this empirical approach shows, the World Bank has indeed reduced extractive funding to the benefit of climate funding after 2019, though this change was not abrupt as much as a culmination of a decade-long trend.

Much has been written about why countries borrow from the International Monetary Fund (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

Coal Plants." *Reuters*.

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

[5]World Bank Group. 2017. *Press Release: World Bank Group Announcements at One Planet Summit.*

[6]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.

consolidation often comes at the expense of the environment, as loans are associated with a significant increase in deforestation. 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). Though the two Bretton Woods institutions have overlapping tasks (Marchesi and Sirtori, 2011), 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 almost never 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 relative flexibility means the Bank might be better positioned to provide climate finance, as long as it is willing to do so.

Initially, this study connects multilateral lending to climate politics and extractive industries, explaining how IOs might 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). Following this literature review, the study provides descriptive information about the content of World Bank projects, using keyword-assisted topic models (Eshima, Imai and Sasaki, 2024) to identify each project's extractive and climate components. Linear regressions show a significant reduction in the extractive topic after 2019, paired with a relative (but not absolute) increase in the climate topic. This reflects a decline in oil and gas lending across the board, even where natural resources are highly salient. The conclusion outlines the next steps to deepen this research agenda.

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.[7] 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 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)

[7]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.

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 arguably 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). 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). If World Bank staff cares about the environment, has relative discretion over how to distribute loans, and directly influences loan implementation, these loans should take climate issues seriously.

Even 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. 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. It is possible that World Bank leadership supports 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

Extractive industries move exponentially more money than multilateral lending. In 2023, the World Bank Executive Board approved 322 projects worth a modest $72.8 *billion*, whereas mineral fuel and oil exports moved a total of $1.89 *trillion*.[8] 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

[8] 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."

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 — 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. I use the case of EITI to illustrate IOs' involvement in extractive industries.

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. Initially, EITI adherence was seen as 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). Today, its perceived reputational benefits are much broader, even if evidence of its 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.[9] The choice to continuously support these projects, rather than advise borrowers to 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 will 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.

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.[10] In light of these projections, concerns about a poorly-

[9] 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.

[10] World Development Indicators 2024.

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.[11] As an illustration, Guyana's president Irfaan Ali declared in 2023: "53% of the world energy mix 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."[12] 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."[13] 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. With these legitimacy concerns in mind, it is possible that the World Bank continues 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

[11] 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*.

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

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

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 decline in oil and gas financing after 2019 — or, 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 Descriptive Analysis

4.1 World Bank Project Data

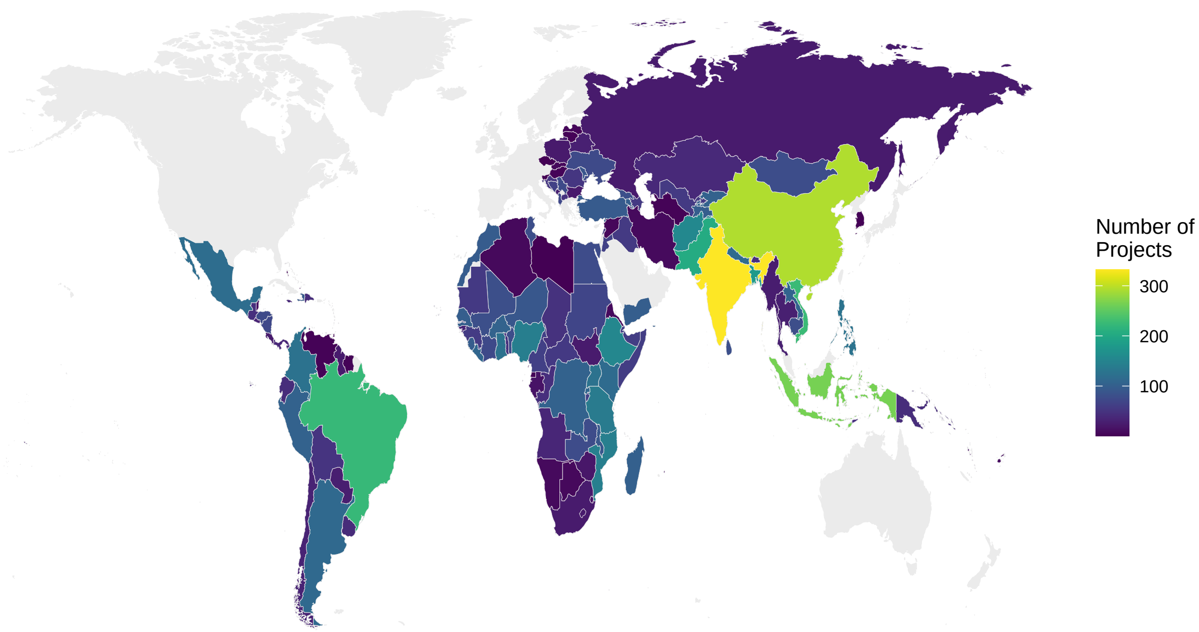
I use data on all projects approved by the World Bank Executive Board from January 2001 to December 2022,[14] excluding projects that were dropped, cannot be attributed to one single sovereign state, are funded by multi-donor trust funds (i.e. not directly funded by the World Bank), and have no lending instrument or clear approval date. Figure 1 breaks down the number of approved projects by country.

The World Bank can purchase emissions reductions, offer guarantees to mobilize private sector investment, and provide funding to buy back commercial debt. These activities are excluded from the analysis, as they are not technically loans. Instead, I focus on the three lending instruments offered to governments (Heinzel and Liese, 2021).[15] 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.

[14] World Bank project information is available since May 1947, but the independent variables (discussed in Section 5.2) are not. A total of 9,194 projects meet the selection criteria, but I exclude those for which any independent variable is missing. The analysis includes the remaining 9,101 projects.

[15] Like Winters (2010, 431, fn 34), Heinzel and Liese (2021, 628, fn1), and many others, I speak of "lending" even when projects have a grant component.

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



This map shows the number of projects approved by the World Bank Executive Board, by country, between 2001 and 2022. This excludes projects that were dropped, cannot be attributed to one single sovereign state, are funded by multi-donor trust funds (i.e. not directly funded by the World Bank), and have no lending instrument or clear approval date.

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).

Most of the projects included in the analysis have a clear title and development objective — for example, to "mobilize private investments through the piloting of a sustainable solar and battery energy storage system competitive bidding process" or "strengthen the capacity

[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.

of the Federal Government of Somalia to manage its petroleum sector."[17] I combine each project's title and development objective into one single description, translating it into English and correcting typos if necessary. Then, I preprocess the text: I lowercase all letters and remove punctuation, numbers, separators, and stopwords, but do not stem words to avoid the risk of combining words with substantively different meanings (Denny and Spirling, 2018). Finally, I use the preprocessed description to classify each project according to its content.

4.2 Classifying Projects

There are 11 official World Bank project sectors,[18] ranging from *Agriculture* (with subsectors like crops, irrigation, forestry, and livestock) to *Water/Sanitation/Waste* (with subsectors like waste management and water supply). Zeitz (2021) distinguishes between "hard" sectors (such as water supply, sanitation, transportation, agriculture, mining, and industry) and "soft" sectors (such as health and education). But one challenge is that projects do not always fit squarely into one single sector. For example, a project whose development objective is "to improve mental health and psychosocial wellbeing of children and adolescents in selected schools" is related to health, but also education. Another project's subcomponents — "drainage, boreholes, road repair, essential drugs, malnutrition alleviation, essential school supplies, lines of credit for productive purposes" — covers infrastructure, transportation, health, education, and non-specified credit. To circumvent this issue, Zeitz (2021) codes projects as belonging to the "hard" sector when its largest sector is one of the abovementioned ones, as labelled by the World Bank. This makes sense when looking at "hard" sectors in the aggregate, but I focus on one specific sector for which there is arguably an incentive to provide erroneous labels. Projects that are seemingly unrelated to natural resources and

[17] Though the World Bank consolidates information about all lending projects into one spreadsheet, sometimes the development objective and lending instrument are missing. In these cases, I scrape the corresponding Project Appraisal Document or Project Performance Assessment Report. When these documents are not available, I only work with the project title.

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

were not labeled as such could still "hide" a natural resource component, allowing the World Bank to support the extractive sector without violating its pledge to cease direct funding of oil and gas projects. Another challenge is that the Bank does not always label its projects with diligence: many projects have no sector labels. Since I am interested in one specific type of "hard" sector, the extractive sector, I need a coding that is more granular.

Rather than manually code each project according to its content or revisit the World Bank's incomplete labeling, I thus estimate a topic model, capturing the relative importance of different topics within one single project. Specifically, I use Eshima, Imai and Sasaki's (2024) keyword assisted topic model (keyATM), which has previously been used to classify conditionality from the World Bank (Cormier and Manger, 2022) and the IMF (Goes, 2023).

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 explains the word distributions. In identifying a set 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. I estimate a dynamic keyATM, an extension of the model that uses a Hidden Markov Model to incorporate time ordering. This allows researchers to investigate how the prevalence of each topic changes over time.

To estimate a dynamic keyATM, I use the 11 aforementioned project sectors as topics and their corresponding subsectors as keywords, with some differences. In the original World Bank taxonomy, the *Energy and Extractives* sector does not distinguish between non-renewables and renewables. Given my research question, I divide this sector into two separate topics: *Extractives* includes keywords like "oil," "gas," "petroleum," and "eiti" (lowercased), whereas *Climate and Renewables* includes keywords like "renewable," "solar," "wind," and "hydropower." I also include an *Environment* topic, consisting of keywords like "nature," "forest," "biodiversity," and "gef" (lowercase, indicating the Global Environment Facility),[19] and a residual topic with no keywords to absorb content that does not fall under any existing category (see appendix for list of all keywords, all topics, and most common words per topic).

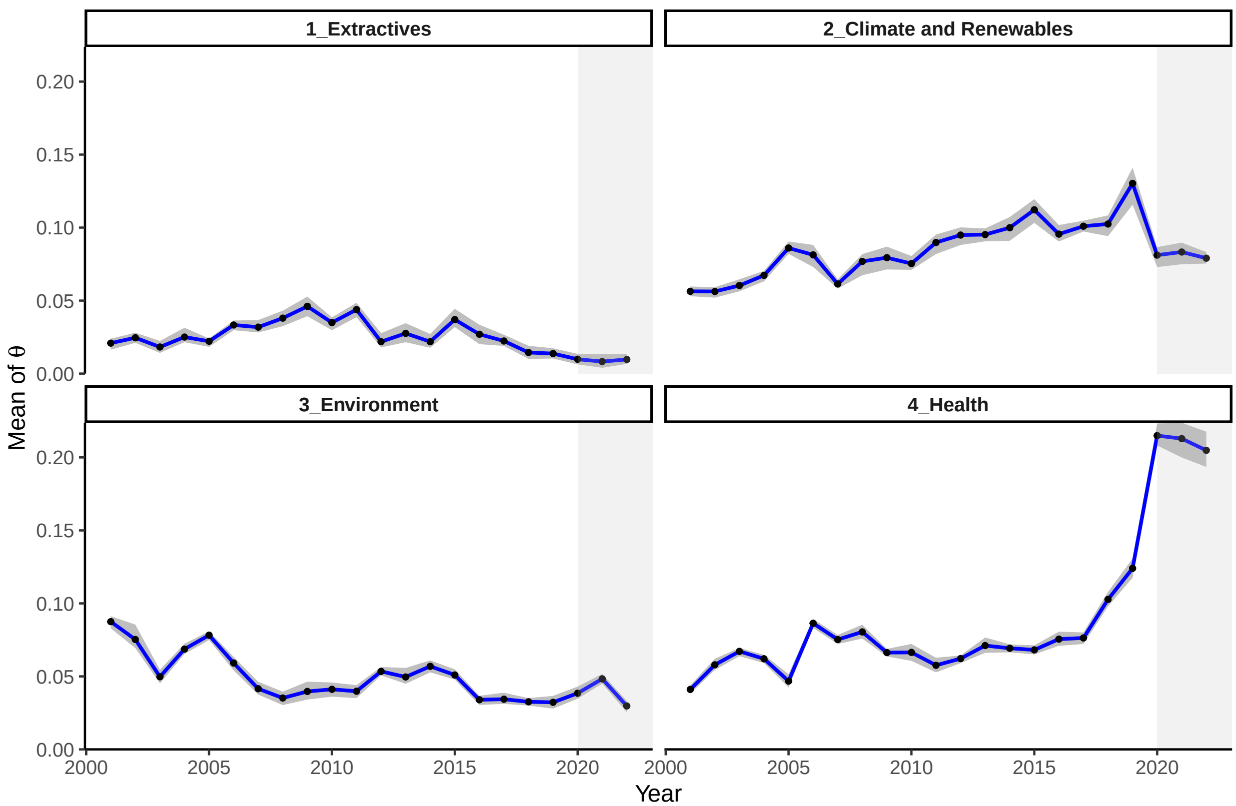
Table 1 presents the top ten words for three relevant topics: *Extractives*, *Climate and Renewables*, and *Environment*. A fourth topic, *Health*, serves as a placebo, confirming that the top words associated with each topic define a meaningful theme, even beyond the topics of interest. The pre-specified keywords correctly matched to the pre-specified topic are in bold; one keyword, "service," is among the top ten words for *Health* despite having

[19] While the dataset excludes projects funded by multi-donor trust funds like GEF, several projects are funded directly by the World Bank in the context of a broader GEF initiative.

Table 1: Most Common Words Per Topic

Extractives	Climate and Renewables	Environment	Health
eiti	energy	management	**health**
support	development	conservation	response
gas	electricity	sustainable	emergency
million	power	**forest**	**covid-19**
implementation	**climate**	**environmental**	services*
mining	efficiency	**biodiversity**	financing
additional	**renewable**	developmental	additional
grant	resilience	**gef**	development
financing	increase	areas	support
oil	improve	natural	crisis

Figure 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.

been originally assigned to the topic *Industry and Trade/Services*. The project with the highest prevalence for *Extractive* is titled "Senegal Support to EITI Compliance Process" (Senegal, 2016). The project with the highest prevalence for *Climate and Renewables* is titled "Additional Financing: Rooftop Solar Program for Residential Sector" (India, 2022).

In Figure 2, each panel presents θ, the relative prevalence of a topic, averaged for all 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, less than five percent of the vocabulary was related to *Extractives*; a similar percentage was related to *Climate and Renewables*, whereas nearly ten percent pertained to *Environment*. Over time, there has been a gradual, consistent decline in the *Extractives* and *Environment*. In these sectors, there was no abrupt change after 2019, only a continuation of already existing trends. Meanwhile, the vocabulary related to *Climate and Renewables* increased up to 2019 before declining starkly in 2020. In contrast, the vocabulary associated with the health sector increased since the COVID-19 pandemic in 2020, suggesting that World Bank project priorities respond quickly to current events and again confirming that the model is doing a good job of parsing out different topics. Of course, the model does not say whether the topic proportions in Figure 2 changed significantly or whether these changes are significantly related to specific external factors. This is what I explore in the next session: I seek to understand whether there was any meaningful change in the vocabulary of World Bank projects after 2019, even after accounting for other factors.

5 Predicting Variation in Topic Prevalence Over Time

5.1 Empirical Strategy

Since the unit of analysis is a World Bank project, the data do not follow a balanced panel structure. There might be multiple observations for the same country and year, just one, or none at all. Therefore, I follow Cormier and Manger (2022) — who work with the same data structure — and estimate four separate linear regressions. In each model, the dependent variable is one of the four topic proportions in Figure 2, converted to a percentage for ease of interpretation. All models include standard errors clustered two ways, by country and year. 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). In the appendix, I present similar models for the remaining topics.

Still, topic proportions are compositional outcomes in a zero-sum, trade-off relationship: when one topic proportion increases, the total proportion of other topics necessarily declines. These proportions are inherently correlated: they must add up to one. Modeling them separately ignores this correlation, which can lead to biased or inefficient estimates (Philips, Rutherford and Whitten, 2016). To account for this compositional nature, I follow Tomz, Tucker and Wittenberg (2002) and estimate a second set of models: seemingly unrelated regressions (SUR) with a log-ratio transformation of the outcomes. Specifically, I calculate the log of each topic proportion relative to that of the baseline topic, *Extractive*. The logged ratio of *Climate and Renewables* to *Extractives*, for example, quantifies changes in the climate vocabulary *relative* to the extractive vocabulary, whereas the logged ratio of *Environment* to *Extractives* does the same for environmental terms *relative* to extractive terms. The resulting coefficients indicate how a one-unit change in each independent variable alters the log ratio for a particular topic. Admittedly, this approach is less straightforward to interpret, but it works well in combination with the separate regressions. My empirical results highlight not only how the content of World Bank projects change over time, but also how some sectors gain more attention at the expense of others.

5.2 Independent Variables

Existing research tends to examine the number, size, and conditionality of World Bank projects, not their content. Yet the project content is plausibly explained by similar factors:

a mix of recipient conditions and donor interests (Cormier and Manger, 2022), all lagged to avoid simultaneity bias.[20]

My main goal is to understand whether the content of World Bank projects changed significantly after 2019, as indicated by the dichotomous variable *After 2019*. Beyond that, 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 and project-specific (Winters, 2010). To measure the recipient's quality of governance, I 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), *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* words might be more prevalent among EITI members; *Climate and Renewables* and *Environment* words might be more prevalent among SIDS (which tend to be more vulnerable to climate change) or in 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 *Natural 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 projects with a larger *Extractive* content, even after 2019. *DAC Aid* indicates the total official development assistance received from members of the Development Assistance Com-

[20] For now, I exclude several important independent variables due to their limited coverage for recent years. For example, data on financial crises (Nguyen, Castro and Wood, 2022; Laeven and Valencia, 2020) or oil and gas field discoveries (Cust, Mihalyi and Rivera-Ballesteros, 2021; Horn, 2014) end in 2019 and 2020, respectively.

mittee (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, I 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 Participation* (Kentikelenis and Stubbs, 2023) and another denotes *UN Security Council Membership* (Dreher, Sturm and Vreeland, 2009*a*); using the IMF and UN websites, respectively, I 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, it is possible that US allies are more likely to fall under the "exceptional circumstance" category.

5.3 Results

To understand what explains variation in the content of World Bank projects, Table 2 presents the results of four linear regressions, examining the four main topic proportions separately. Relative to a project approved between January 2001 and December 2019, a project approved after December 2019 used 2.25 percent fewer words related to the extractive sector, 1.29 percent fewer words related to climate and renewables, and 13.01 percent more words related to health, all else equal. These effects are statistically significant. In contrast, there was no significant change in the use of words like "nature," "forest," "reforestation," "biodiversity," "marine," and others associated with the *Environment* topic.

Table 2: Predictors of Topic Prevalence Over Time, 2001–2022 (Linear Regressions)

	Dependent Variable:			
	% Extractives	% Climate and Renewables	% Environment	% Health
	(1)	(2)	(3)	(4)
After 2019	-2.25^{***}	-1.29^{**}	-0.65	13.01^{***}
	(0.36)	(0.59)	(0.58)	(1.05)
Governance	0.22	3.32^{***}	1.17^{*}	-3.15^{***}
	(0.39)	(0.91)	(0.67)	(0.94)
Election Year	0.35	0.11	-0.56	-0.65^{*}
	(0.24)	(0.58)	(0.40)	(0.38)
EITI Member	1.76^{***}	-0.18	-0.49	-0.09
	(0.50)	(0.91)	(0.66)	(0.84)
SIDS	1.14^{*}	6.06^{***}	-1.51	2.92^{**}
	(0.59)	(2.13)	(1.05)	(1.25)
Disaster	0.16	-0.37	0.99	-0.02
	(0.30)	(0.81)	(0.70)	(0.59)
Log GDP per Capita	-0.31	-0.20	1.38^{***}	-1.71^{***}
	(0.23)	(0.53)	(0.40)	(0.56)
Log Resource Rents	0.18^{*}	-0.36	0.55^{***}	0.04
	(0.09)	(0.34)	(0.16)	(0.25)
DAC Aid	-0.10	0.53^{*}	-0.36^{***}	-0.68^{*}
	(0.08)	(0.28)	(0.13)	(0.37)
Chinese Finance	-0.01	-0.03	-0.04	0.00
	(0.03)	(0.07)	(0.05)	(0.05)
IMF Program	0.59	-2.09^{***}	-0.08	-0.34
	(0.39)	(0.45)	(0.40)	(0.68)
UNSC Member	-0.05	-1.38	0.10	0.26
	(0.32)	(1.17)	(0.80)	(0.96)
Voting with the US	-1.18	6.38	-3.34	0.12
	(2.26)	(5.32)	(3.54)	(4.07)
Intercept	4.21^{**}	12.01^{***}	-5.35	18.77^{***}
	(2.02)	(4.00)	(3.31)	(4.65)
R^2	0.01	0.02	0.01	0.05
Observations	9,101	9,101	9,101	9,101

This table presents the results of four linear regressions. In each regression, the dependent variable is the prevalence of the corresponding topic, converted to a percentage. All independent variables are lagged at $t-1$. Standard errors clustered by country and year. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Unsurprisingly, EITI members, SIDS, and those with a large GDP share coming from resource rents tend to attract projects with a significantly larger *Extractive* vocabulary. Models 2 and 3 connect a larger *Climate and Renewables* or *Environment* vocabulary to a higher quality of governance. Model 4 suggests that the share of *Health* increases in contexts of poor governance and low GDP per capita. In the appendix, I present additional results using the official World Bank sector labels as the outcome of interest; though these labels are far less granular, the results are almost identical.

Table 3: Predictors of Topic Prevalence Over Time, 2001–2022 (Seemingly Unrelated Regressions)

	Dependent Variable:		
	$Log\left(\frac{Climate}{Extractives}\right)$	$Log\left(\frac{Environment}{Extractives}\right)$	$Log\left(\frac{Health}{Extractives}\right)$
	(1)	(2)	(3)
After 2019	0.42***	0.23***	2.02***
	(0.10)	(0.09)	(0.11)
Governance	0.49***	0.14*	−0.44***
	(0.08)	(0.07)	(0.09)
Election Year	−0.12	−0.21***	−0.12
	(0.08)	(0.07)	(0.08)
EITI Member	−0.30***	−0.30***	−0.21**
	(0.09)	(0.08)	(0.10)
SIDS	0.72***	−0.33***	0.14
	(0.13)	(0.12)	(0.14)
Disaster	−0.04	0.12	−0.01
	(0.09)	(0.08)	(0.09)
Log GDP per Capita	0.03	0.24***	−0.13***
	(0.05)	(0.04)	(0.05)
Log Resource Rents	−0.05**	0.04*	−0.06**
	(0.02)	(0.02)	(0.03)
DAC Aid	0.07**	−0.05*	−0.08**
	(0.03)	(0.03)	(0.03)
Chinese Finance	−0.01	−0.00	0.00
	(0.01)	(0.01)	(0.01)
IMF Program	−0.37***	−0.17***	−0.11
	(0.07)	(0.06)	(0.08)
UNSC Member	−0.19	−0.02	−0.06
	(0.13)	(0.12)	(0.14)
Voting with the US	1.10***	0.12	0.99**
	(0.42)	(0.37)	(0.44)
Intercept	0.73*	−1.43***	1.32***
	(0.39)	(0.35)	(0.42)
R^2	0.03	0.02	0.05
Observations	9,101	9,101	9,101

This table presents the results of three out of 12 seemingly unrelated regressions (the remaining nine are reported in the appendix). In each regression, the dependent variable is the log of a topic proportion relative to the proportion of the baseline topic, *Extractive*. All independent variables are lagged at $t-1$. To capture correlated interdependencies, standard errors are allowed to be correlated across equations. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Still, Table 2 says little about trade-off relationships. With separate regressions, the interpretation is restricted to the individual components rather than the compositional relationships: researchers can only say how an independent variable affects each component separately, not how changes in one component affect others. Separate regressions do not allow for a direct analysis of how changes in one topic relate to changes in another topic. For example, EITI members and SIDS might have a higher topic proportion for *Extractives*, but I cannot directly infer which sector is "losing" words to the extractive sector unless I explicitly model the relationships between topics using SUR. This is what I do in Table 3.

Since the topic model produces 13 topics, the SUR approach consists of 12 regressions. Table 3 presents the change in *Climate and Renewables*, *Environment*, and *Health* relative to the baseline topic, *Extractives*; I report the remaining nine regressions in the appendix. The coefficients represent the expected change in the log-ratio of each component relative to the baseline for a one-unit change in the independent variables. A positive coefficient denotes an increase in these topic proportions relative to *Extractives*, whereas a negative coefficient denotes a decrease relative to *Extractives*.

Looking at the separate regressions alone, one might worry that the World Bank did not deliberately divest from the oil and gas sector after 2019 as much as it shifted all resources across all sectors to fight the COVID-19 pandemic — hence the substantial increase in *Health* shown in Table 2. In Table 3, the compositional models indeed suggest that *Extractive* "lost" significant real estate to *Health*. In Model 3, the coefficient for *After 2019* is 2.02, which, when exponentiated, results in approximately 7.54. In the period following 2019, there was a 7.54-time increase in the ratio of words discussing the health sector relative to words discussing the extractive sector compared to the period until 2019. But *Extractive* also "lost" words to *Climate and Renewables* and *Environment*. In absolute terms, World Bank projects might have reduced their focus on *Climate and Renewables* after 2019, but *relative to the extractive sector*, this focus actually increased by approximately 52 percent.[21] Put simply, World Bank projects are using fewer words like "oil," "gas," or "mining" — significantly replacing them with words like "health," "response," "emergency," and "covid-19," as one would expect in light of the pandemic, but also words like "climate," "renewable," and "resilience." To a small but significant extent, projects are less likely to have a fossil fuel component and more

[21] This is the exponentiated coefficient for *After 2019* in Model 1: $e^{0.42} = 1.52$.

likely to have a green component after 2019, all else equal.

As before, EITI membership and a larger GDP share coming from resource rents are associated with a significant relative increase in *Extractives*, as is IMF program participation, reflecting the fact that the IMF puts a premium on good natural resource management (Goes and Chapman, 2024; Goes, 2023). Interestingly, across 12 SUR, the effect of *Chinese Finance* is never significant: Chinese competition does not prompt the World Bank to shift its project focus toward or away from natural resources. It is still possible that traditional donors emulate new donors like China by increasing infrastructure spending (Zeitz, 2021), but this is likely to happen for "hard" sectors in the aggregate, not for the extractive sector in particular.

5.4 Exploring Heterogeneity in Extractive Financing After 2019

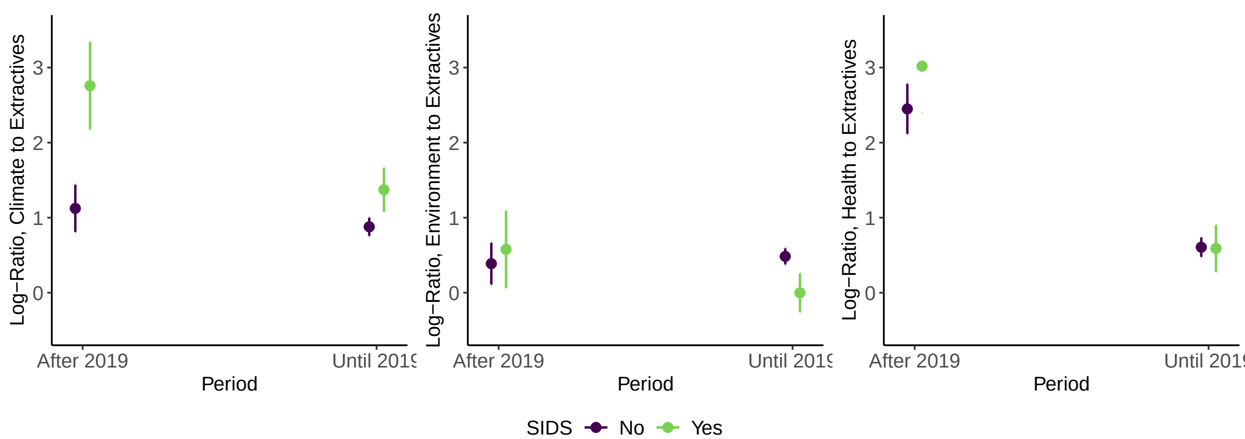
Table 4: Predictors of Topic Prevalence Over Time, 2001–2022 (Seemingly Unrelated Regressions, Including Interaction Effects)

	Dependent Variable:		
	$Log\left(\frac{Climate}{Extractives}\right)$	$Log\left(\frac{Environment}{Extractives}\right)$	$Log\left(\frac{Health}{Extractives}\right)$
	(1)	(2)	(3)
After 2019	−0.21	−0.46	3.34***
	(1.19)	(1.05)	(1.27)
Governance	0.49***	0.16*	−0.45***
	(0.09)	(0.08)	(0.10)
Election Year	−0.13	−0.23***	−0.12
	(0.09)	(0.08)	(0.09)
EITI Member	−0.25**	−0.39***	−0.17
	(0.10)	(0.09)	(0.11)
SIDS	0.49***	−0.48***	−0.02
	(0.15)	(0.13)	(0.16)
Disaster	−0.00	0.14*	0.03
	(0.10)	(0.09)	(0.10)
Log GDP per Capita	0.03	0.23***	−0.12**
	(0.05)	(0.04)	(0.05)
Log Natural Resource Rents	−0.06**	0.04	−0.04
	(0.03)	(0.02)	(0.03)
DAC Aid	0.07**	−0.04	−0.06*
	(0.03)	(0.03)	(0.04)
Chinese Finance	−0.01	0.00	0.00
	(0.01)	(0.01)	(0.01)
IMF Program	−0.39***	−0.16**	−0.14*
	(0.08)	(0.07)	(0.08)
UNSC Member	−0.21	−0.14	−0.07
	(0.14)	(0.13)	(0.15)
Voting with the US	1.20***	0.08	1.13**
	(0.45)	(0.40)	(0.48)
After 2019 × Governance	−0.05	−0.26	0.07
	(0.24)	(0.21)	(0.25)
After 2019 × Election Year	0.15	0.08	−0.00
	(0.22)	(0.19)	(0.23)
After 2019 × EITI Member	−0.26	0.41**	−0.15
	(0.23)	(0.20)	(0.25)
After 2019 × SIDS	1.14***	0.67**	0.59*
	(0.33)	(0.30)	(0.36)
After 2019 × Disaster	−0.27	−0.21	−0.07
	(0.26)	(0.23)	(0.28)
After 2019 × Log GDP per Capita	0.09	0.05	−0.11
	(0.14)	(0.12)	(0.15)
After 2019 × Log Natural Resource Rents	0.09	0.00	−0.14*
	(0.07)	(0.06)	(0.07)
After 2019 × DAC Aid	0.07	−0.08	−0.27*
	(0.14)	(0.12)	(0.14)
After 2019 × Chinese Finance	0.04	−0.00	−0.03
	(0.04)	(0.03)	(0.04)
After 2019 × IMF Program	0.24	−0.11	0.36
	(0.22)	(0.20)	(0.24)
After 2019 × UNSC Member	0.10	0.86**	0.04
	(0.39)	(0.35)	(0.42)
After 2019 × Voting with the US	−1.16	0.53	−1.07
	(1.20)	(1.06)	(1.27)
Intercept	0.76*	−1.35***	1.14**
	(0.43)	(0.38)	(0.45)
R^2	0.03	0.02	0.05
Observations	9,101	9,101	9,101

This table presents the results of three out of 12 seemingly unrelated regressions (the remaining nine are reported in the appendix). In each regression, the dependent variable is the log of a topic proportion relative to the proportion of the baseline topic, *Extractive*. All independent variables are lagged at $t-1$. To capture correlated interdependencies, standard errors are allowed to be correlated across equations. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 3 suggests that the World Bank followed its pledge to reduce oil and gas funding after 2019, except in "exceptional circumstances." What qualifies as an "exceptional circumstance?" To answer this question, I interact *After 2019* with all other predictors in Table 4. As before, I report the results for *Climate and Renewables*, *Environment*, and *Health* (relative to *Extractives*) here, with the remaining topics in the appendix.

Figure 3: Predicted Values, 2001–2022



Based on Models 1, 2, and 3 in Table 4, these plots display the predicted values of each dependent variable until 2019 and after 2019, conditional on *SIDS*, with 90 percent confidence intervals. Compared to non-SIDS, World Bank projects in SIDS consistently receive a higher share of climate words relative to extractive words, but this difference became even more pronounced after 2019.

Given the challenge of interpreting a fully interacted model, Figure 3 presents the most significant interaction: *After 2019* × *SIDS*. Compared to other states, small island developing states consistently receive a higher share of climate words relative to extractive words, but this difference became even more pronounced after 2019. This gap is intuitive: SIDS have fewer resources and are more vulnerable to climate change. In these contexts, the extractive sector is understandably not a priority. After 2019, the shift away from *Extractives* and toward *Environment* was more pronounced among EITI members or members of the UN Security Council, whereas the shift away from *Extractives* and toward *Health* was less pronounced in countries with a large GDP share of natural resource rents or sizable DAC aid flows. Other than that, no other factors significantly moderate the effect of *After 2019*, suggesting that changes in this period tended to occur across the board.

6 Conclusion

This study shows that the World Bank reduced financing to projects in the oil and gas sectors after 2019. As expected, much of this finance went to the health sector to combat the COVID-19 pandemic, but at least some of it was divested to projects related to renewable energy and climate mitigation. Of course, linear regressions alone cannot say if this change was a direct consequence of the World Bank's climate pledge or if it just reflects a much longer fossil fuel divestment trend. Additional qualitative evidence will probe whether the pledge to cease oil and gas funding after 2019 implied a hard cutoff or was just a culmination of existing funding priorities. To be clear, extractive finance did not stop altogether after 2019. True to its word, the World Bank continued to fund such projects in exceptional circumstances. Expert interviews will provide further insights into the Bank's decision-making process.

In quantitative terms, I aim to explore other outcomes — not just the proportion of extractive projects approved by the World Bank each year but also their duration and funding amount. The Bank might continue to fund extractive projects but provide much smaller amounts for shorter periods, which would still signal a growing commitment to climate policy. Additionally, the regional distribution of projects might shed light on potential geographical priority shifts that align with the World Bank's stated goals.

I also plan to pursue other empirical strategies, like a regression discontinuity design (RDD) with December 2019 as a cutoff. The control group would consist of projects approved until this date (pre-policy change), whereas the treatment group would consist of projects approved after this date (post-policy change). One potential challenge is that an RDD assumes there was no manipulation of the assignment variable around the cutoff — for example, it assumes that the World Bank did not strategically accelerate the approval of extractive projects to meet the cutoff. I plan to interview World Bank experts about the timing of project approval, but it is unlikely that they would admit to such project manipulation, even if it did occur.

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. 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. 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
Pledge and Prejudice: The Reality of International Climate Commitments

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Contents

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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 Model Description

To classify the content of World Bank projects, I 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, I 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, Beta$(1, 1)$.

Compared to the base keyATM described above, the extension I 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

I use the following keywords to generate the $\tilde{K} = 12$ topics of interest:

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

Climate and Renewables: renewable, renewables, solar, wind, hydropower, hydroelectric, photovoltaics, biomass, geothermal, climate, ghg, hcfc, hydrochlorofluorocarbons, methane, carbon, sequestration, atmosphere, greenhouse, unfccc

Environment: nature, forest, reforestation, biodiversity, marine, redd, wildlife, environment, environmental, gef

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

Transportation: road, roads, highway, railway, rail, port, airline, transport, transportation

Agriculture: agro, agri, agriculture, irrigation, rural, soil, fertilizer, livestock, farm, farming, land, smallholder, crop, crops, drainage, fisheries, forestry

Education: education, school, schools, student, students, learn, learning, vocational, teaching, teacher, teachers, university, universities, workforce

Finance: banking, insurance, pension, pensions, finance, financial, securities, sme, smes, msme, msme, fiscal

Industry and Trade housing, construction, manufacturing, service, services, infrastructure, trade, tourism, industry, industries

Water, Sanitation, and Waste: water, sanitation, sanitary, waste, wastewater, watershed, sewerage, sewer, drainage

Information and Communication: communication, communications, telecommunications, telecom, ict, digital

Public Administration: law, justice, administration, government, subnational, data, statistics, statistical, capacity, database

D Additional Topics: Prevalence

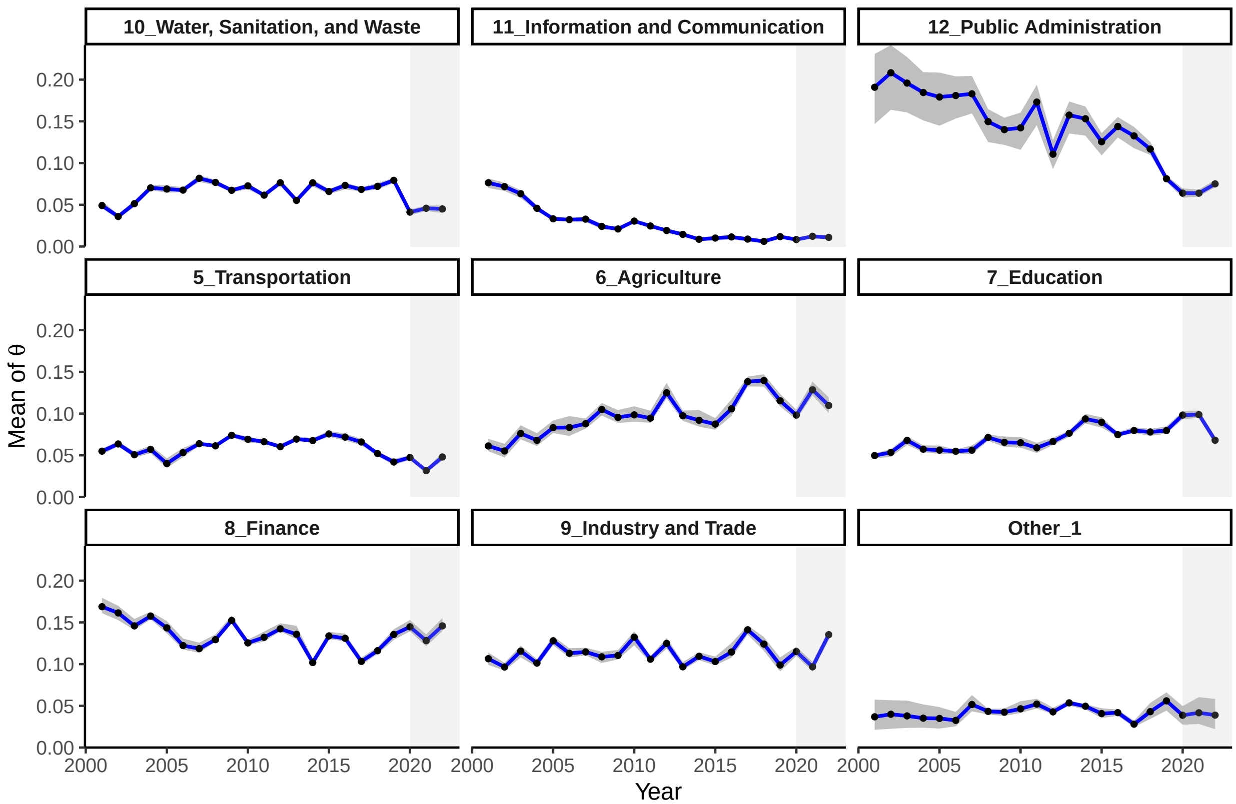
Table D.1 presents the ten most frequent words for all topics other than the four main ones. In Figure D.1, each panel presents θ, the relative prevalence of these topics. The values of θ are averaged for all projects approved by the Executive Board every year between 2001 and 2022. The post-2019 period is shaded in grey.

Table D.1: Most Common Words Per Topic

Water, Sanitation, and Waste	Information and Communication	Public Administration	Transportation
water	satisfactory	**capacity**	**transportation**
sanitation	performance	**government**	**road**
supply	outcome	development	development
management	borrower	public	improve
services*	**digital**	management	**roads**
development	ratings	support	urban
urban	lessons	sector	safety
improve	risk	system	sector
access	credit	building	maintenance
waste	follows	strengthening	infrastructure*

Agriculture	Education	Finance	Industry and Trade	Other
rural	**education**	development	development	social
development	development	sector	**services**	safety
agricultural	quality	policy	**infrastructure**	protection
agriculture	improve	support	urban	poor
land	**learning**	**financial**	local	development
increase	basic	public	access	net
access	access	growth	**service**	youth
sustainable	secondary	**fiscal**	improve	employment
improve	**school**	management	community	support
productivity	primary	reform	social	additional

Figure D.1: 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 Additional Topics: Predictors

Table E.1: Predictors of Topic Prevalence Over Time, 2001–2022 (Linear Regressions)

	Dependent Variable: %								
	Water, Sanitation, and Waste	Information and Communication	Public Administration	Transportation	Agriculture	Education	Finance	Industry and Trade	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
After 2019	−2.42***	−1.39***	−9.66***	−1.70***	1.38	1.66**	1.79**	0.32	1.19***
	(0.11)	(0.39)	(0.93)	(0.58)	(0.89)	(0.71)	(0.83)	(1.33)	(0.34)
Governance	−1.18	0.36	−1.90**	1.92*	0.28	−0.25	5.31***	−4.43***	−1.68***
	(0.87)	(0.27)	(0.97)	(1.00)	(0.87)	(0.65)	(1.50)	(0.73)	(0.45)
Election Year	−0.93	−0.17	1.26*	0.59	−0.15	0.45	0.43	−0.80	0.09
	(0.62)	(0.31)	(0.74)	(0.69)	(0.50)	(0.35)	(0.78)	(0.55)	(0.31)
EITI Member	1.31**	−1.29***	−1.55	−1.21**	0.90	1.82***	−2.17*	−1.03	2.21***
	(0.64)	(0.44)	(1.13)	(0.57)	(0.83)	(0.52)	(1.12)	(0.74)	(0.73)
SIDS	−3.99***	−0.09	−3.19***	0.60	−2.78*	0.46	1.60	−0.69	−0.53
	(0.94)	(0.32)	(1.13)	(1.37)	(1.65)	(1.56)	(2.70)	(1.64)	(1.02)
Disaster	0.38	0.16	−0.87	1.12	0.79	−0.17	−2.19**	0.86	−0.85
	(0.84)	(0.30)	(0.97)	(0.75)	(0.80)	(0.62)	(1.05)	(0.96)	(0.58)
Log GDP per Capita	1.61*	−0.25	1.46**	0.63	−1.86***	−0.45	−0.32	−0.53	0.54
	(0.83)	(0.19)	(0.70)	(0.85)	(0.56)	(0.36)	(0.79)	(0.53)	(0.35)
Log Resource Rents	0.01	−0.06	0.12	0.27*	0.11	−0.32	0.50	−0.80*	−0.24
	(0.14)	(0.06)	(0.31)	(0.16)	(0.23)	(0.23)	(0.43)	(0.42)	(0.16)
DAC Aid	−0.16	−0.01	0.20	0.61*	−0.02	0.19	−0.59*	0.67***	−0.28
	(0.16)	(0.14)	(0.42)	(0.33)	(0.33)	(0.21)	(0.33)	(0.22)	(0.24)
Chinese Finance	0.08	−0.04	−0.07	0.06	0.11	−0.02	−0.12	0.13	−0.04
	(0.10)	(0.02)	(0.13)	(0.10)	(0.09)	(0.03)	(0.09)	(0.09)	(0.04)
IMF Program	−1.56**	0.53*	1.65*	−1.99***	−1.50***	−0.13	4.21***	−0.28	1.00*
	(0.64)	(0.31)	(0.91)	(0.76)	(0.53)	(0.50)	(0.86)	(0.88)	(0.53)
UNSC Member	0.00	1.82**	−0.03	−1.66	−0.13	0.04	1.02	0.61	−0.61
	(1.00)	(0.71)	(1.11)	(1.20)	(1.11)	(0.81)	(1.26)	(1.17)	(0.49)
Voting with the US	−9.21**	−0.78	6.02	2.22	3.24	−9.04***	13.63**	−6.09	−1.97
	(4.30)	(2.25)	(5.85)	(4.71)	(4.55)	(2.72)	(5.82)	(5.07)	(2.09)
Intercept	−3.90	4.81***	4.06	1.25	22.76***	11.20***	16.41***	14.02***	−0.24
	(5.68)	(1.53)	(5.62)	(6.13)	(4.66)	(2.97)	(6.10)	(3.90)	(3.12)

This table presents the results of four linear regressions. In each regression, the dependent variable is the prevalence of the corresponding topic, converted to a percentage. All independent variables are lagged at $t-1$. Standard errors clustered by country and year. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table E.2: Predictors of Topic Prevalence Over Time, 2001–2022 (Seemingly Unrelated Regressions)

	Dependent Variable: Logged...								
	Water / *Extractives*	*ICT* / *Extractives*	*PublicAdmin.* / *Extractives*	*Transportation* / *Extractives*	*Agriculture* / *Extractives*	*Education* / *Extractives*	*Finance* / *Extractives*	*Industry* / *Extractives*	*Other* / *Extractives*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
After 2019	0.04	-0.05	-1.35^{***}	0.25^{***}	0.40^{***}	0.52^{***}	0.44^{***}	0.32^{***}	0.46^{***}
	(0.10)	(0.08)	(0.12)	(0.09)	(0.11)	(0.10)	(0.12)	(0.12)	(0.09)
Governance	-0.15^{*}	0.07	0.03	0.19^{**}	0.08	-0.06	0.67^{***}	-0.48^{***}	-0.18^{**}
	(0.08)	(0.07)	(0.10)	(0.08)	(0.09)	(0.08)	(0.10)	(0.10)	(0.08)
Election Year	-0.20^{***}	-0.06	0.08	-0.05	-0.15^{*}	-0.05	-0.04	-0.17^{*}	-0.04
	(0.08)	(0.07)	(0.09)	(0.07)	(0.09)	(0.08)	(0.09)	(0.09)	(0.07)
EITI Member	-0.17^{*}	-0.57^{***}	-0.78^{***}	-0.33^{***}	-0.32^{***}	0.07	-0.55^{***}	-0.42^{***}	-0.04
	(0.09)	(0.08)	(0.11)	(0.09)	(0.10)	(0.09)	(0.11)	(0.11)	(0.08)
SIDS	-0.75^{***}	-0.26^{**}	-0.62^{***}	-0.08	-0.66^{***}	-0.20	-0.11	-0.40^{***}	-0.36^{***}
	(0.13)	(0.11)	(0.16)	(0.12)	(0.14)	(0.13)	(0.15)	(0.15)	(0.12)
Disaster	0.11	0.03	0.08	0.19^{**}	0.16	-0.01	-0.15	0.16	-0.07
	(0.09)	(0.08)	(0.11)	(0.08)	(0.10)	(0.09)	(0.10)	(0.10)	(0.08)
Log GDP per Capita	0.21^{***}	-0.05	0.26^{***}	0.13^{***}	-0.22^{***}	0.03	0.03	-0.05	0.10^{**}
	(0.04)	(0.04)	(0.06)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)
Log Resource Rents	-0.04	-0.04^{**}	0.00	-0.00	0.00	-0.07^{***}	0.03	-0.14^{***}	-0.07^{***}
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)
DAC Aid	-0.01	0.01	0.01	0.07^{**}	-0.00	0.02	-0.07^{*}	0.11^{***}	-0.02
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)
Chinese Finance	0.01	-0.00	-0.02	0.01	0.01	0.01	-0.01	0.01	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
IMF Program	-0.27^{***}	0.01	0.29^{***}	-0.38^{***}	-0.39^{***}	-0.12^{*}	0.42^{***}	-0.16^{*}	0.03
	(0.07)	(0.06)	(0.09)	(0.07)	(0.08)	(0.07)	(0.09)	(0.09)	(0.07)
UNSC Member	-0.01	0.41^{***}	0.28^{*}	-0.24^{*}	-0.08	0.16	0.21	0.10	-0.11
	(0.13)	(0.11)	(0.16)	(0.13)	(0.15)	(0.13)	(0.16)	(0.16)	(0.12)
Voting with the US	-1.00^{**}	0.34	0.50	0.35	0.82^{*}	-0.68^{*}	1.63^{***}	-0.57	0.12
	(0.41)	(0.35)	(0.50)	(0.39)	(0.46)	(0.41)	(0.49)	(0.49)	(0.38)
Intercept	-0.89^{**}	0.84^{**}	0.81^{*}	-0.62^{*}	2.63^{***}	0.35	1.50^{***}	1.80^{***}	-0.49
	(0.38)	(0.34)	(0.47)	(0.37)	(0.43)	(0.39)	(0.46)	(0.46)	(0.36)
R^2	0.01	0.01	0.03	0.01	0.01	0.01	0.02	0.01	0.01
Observations	9,101	9,101	9,101	9,101	9,101	9,101	9,101	9,101	9,101

This table presents the results of nine out of 12 seemingly unrelated regressions (the remaining three are reported in the main text). In each regression, the dependent variable is the log of a topic proportion relative to the proportion of the baseline topic, *Extractive*. All independent variables are lagged at $t-1$. To capture correlated interdependencies, standard errors are allowed to be correlated across equations. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table E.3: Predictors of Topic Prevalence Over Time, 2001–2022 (Seemingly Unrelated Regressions, Including Interaction Effects)

	Dependent Variable: Logged...								
	Water	*ICT*	*PublicAdmin.*	*Transportation*	*Agriculture*	*Education*	*Finance*	*Industry*	*Other*
	Extractives	*Extractives*	*Extractives*	*Extractives*	*Extractives*	*Extractives*	*Extractives*	*Extractives*	*Extractives*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
After 2019	1.61	0.08	−2.35*	0.59	−1.80	2.54**	−1.57	−0.32	0.46
	(1.16)	(1.02)	(1.42)	(1.12)	(1.31)	(1.16)	(1.39)	(1.39)	(1.08)
Governance	−0.18**	0.09	0.05	0.23***	0.12	−0.06	0.65***	−0.49***	−0.18**
	(0.09)	(0.08)	(0.11)	(0.09)	(0.10)	(0.09)	(0.11)	(0.11)	(0.08)
Election Year	−0.24***	−0.10	0.07	−0.05	−0.16*	−0.08	−0.06	−0.17*	−0.05
	(0.08)	(0.07)	(0.10)	(0.08)	(0.09)	(0.08)	(0.10)	(0.10)	(0.08)
EITI Member	−0.28***	−0.72***	−1.02***	−0.36***	−0.44***	0.10	−0.59***	−0.59***	−0.12
	(0.10)	(0.09)	(0.12)	(0.10)	(0.11)	(0.10)	(0.12)	(0.12)	(0.09)
SIDS	−0.84***	−0.33***	−0.67***	−0.19	−0.69***	−0.24*	−0.18	−0.22	−0.47***
	(0.14)	(0.13)	(0.18)	(0.14)	(0.16)	(0.14)	(0.17)	(0.17)	(0.13)
Disaster	0.15	0.05	0.07	0.24***	0.16	−0.02	−0.09	0.18	−0.01
	(0.09)	(0.08)	(0.12)	(0.09)	(0.11)	(0.09)	(0.11)	(0.11)	(0.09)
Log GDP per Capita	0.24***	−0.06	0.25***	0.14***	−0.26***	0.06	−0.01	−0.05	0.10**
	(0.05)	(0.04)	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.04)
Log Natural Resource Rents	−0.04	−0.05**	−0.01	0.01	0.01	−0.08***	0.00	−0.16***	−0.08***
	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
DAC Aid	−0.02	0.01	0.01	0.07**	0.00	0.02	−0.07*	0.10**	−0.01
	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)
Chinese Finance	0.01	−0.00	−0.01	0.01	0.01	0.00	−0.01	0.02	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
IMF Program	−0.31***	−0.00	0.36***	−0.39***	−0.44***	−0.13*	0.44***	−0.21**	−0.02
	(0.08)	(0.07)	(0.09)	(0.07)	(0.09)	(0.08)	(0.09)	(0.09)	(0.07)
UNSC Member	−0.05	0.49***	0.25	−0.26*	−0.09	0.24*	0.23	0.14	−0.08
	(0.14)	(0.12)	(0.17)	(0.13)	(0.16)	(0.14)	(0.17)	(0.17)	(0.13)
Voting with the US	−1.14***	0.41	0.36	0.18	1.03**	−0.70	1.89***	−0.90*	0.12
	(0.44)	(0.38)	(0.54)	(0.42)	(0.50)	(0.44)	(0.53)	(0.53)	(0.41)
After 2019 × Governance	0.19	−0.10	−0.30	−0.31	−0.25	0.07	0.09	0.13	0.03
	(0.23)	(0.20)	(0.28)	(0.22)	(0.26)	(0.23)	(0.27)	(0.27)	(0.21)
After 2019 × Election Year	0.23	0.15	−0.06	0.05	−0.02	0.21	0.15	−0.05	0.09
	(0.21)	(0.18)	(0.26)	(0.20)	(0.24)	(0.21)	(0.25)	(0.25)	(0.20)
After 2019 × EITI Member	0.45**	0.71***	1.17***	0.25	0.52**	−0.18	0.11	0.68**	0.34
	(0.22)	(0.20)	(0.27)	(0.22)	(0.25)	(0.23)	(0.27)	(0.27)	(0.21)
After 2019 × SIDS	0.51	0.36	0.20	0.54*	0.16	0.30	0.27	−0.71*	0.54*
	(0.33)	(0.29)	(0.40)	(0.31)	(0.37)	(0.33)	(0.39)	(0.39)	(0.30)
After 2019 × Disaster	−0.28	−0.17	−0.10	−0.31	−0.05	0.13	−0.60*	−0.23	−0.42*
	(0.26)	(0.22)	(0.31)	(0.25)	(0.29)	(0.26)	(0.31)	(0.31)	(0.24)
After 2019 × Log GDP per Capita	−0.26*	−0.03	0.05	−0.09	0.27*	−0.28**	0.35**	−0.00	0.00
	(0.14)	(0.12)	(0.17)	(0.13)	(0.15)	(0.14)	(0.16)	(0.16)	(0.13)
After 2019 × Log Natural Resource Rents	−0.01	−0.00	0.04	−0.11*	−0.03	0.03	0.18**	0.09	0.05
	(0.07)	(0.06)	(0.08)	(0.07)	(0.08)	(0.07)	(0.08)	(0.08)	(0.06)
After 2019 × DAC Aid	0.08	−0.04	0.08	0.01	−0.05	0.05	0.10	0.24	0.02
	(0.13)	(0.12)	(0.16)	(0.13)	(0.15)	(0.13)	(0.16)	(0.16)	(0.12)
After 2019 × Chinese Finance	0.08**	0.02	−0.01	0.02	−0.01	0.01	−0.01	−0.03	0.00
	(0.04)	(0.03)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
After 2019 × IMF Program	0.21	−0.03	−0.75***	0.03	0.29	0.08	−0.14	0.22	0.33
	(0.22)	(0.19)	(0.27)	(0.21)	(0.25)	(0.22)	(0.26)	(0.26)	(0.20)
After 2019 × UNSC Member	0.21	−0.66**	0.12	0.16	0.03	−0.66*	−0.16	−0.32	−0.23
	(0.38)	(0.33)	(0.47)	(0.37)	(0.43)	(0.38)	(0.46)	(0.46)	(0.35)
After 2019 × Voting with the US	1.29	−0.37	1.45	1.39	−1.04	−0.23	−2.22	2.64*	−0.17
	(1.17)	(1.02)	(1.43)	(1.13)	(1.32)	(1.17)	(1.40)	(1.40)	(1.08)
Intercept	−1.07***	0.89**	0.95*	−0.69*	2.97***	0.10	1.70***	1.89***	−0.50
	(0.41)	(0.36)	(0.51)	(0.40)	(0.47)	(0.42)	(0.50)	(0.50)	(0.39)
R^2	0.02	0.01	0.04	0.02	0.01	0.01	0.02	0.02	0.01
Observations	9,101	9,101	9,101	9,101	9,101	9,101	9,101	9,101	9,101

This table presents the results of three out of 12 seemingly unrelated regressions (the remaining nine are reported in the appendix). In each regression, the dependent variable is the log of a topic proportion relative to the proportion of the baseline topic, *Extractive*. All independent variables are lagged at $t-1$. To capture correlated interdependencies, standard errors are allowed to be correlated across equations. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

F Robustness: Replacting Topic Proportions with Project Sectors

Table F.1: Predictors of Project Sector Over Time, 2001–2022 (Linear Regressions)

	Dependent Variable:		
	Sector: Extractives	Sector: Climate and Renewables	Sector: Health
	(1)	(2)	(3)
After 2019	-0.45^{***}	-0.18^{*}	0.67^{***}
	(0.09)	(0.09)	(0.09)
Governance	0.07	0.40^{**}	-0.05
	(0.10)	(0.17)	(0.09)
Election Year	0.29^{***}	-0.15^{*}	-0.05
	(0.09)	(0.09)	(0.10)
EITI Member	0.42^{***}	-0.04	-0.11
	(0.10)	(0.19)	(0.09)
SIDS	0.14	-0.00	0.01
	(0.17)	(0.27)	(0.12)
Disaster	-0.04	-0.07	-0.02
	(0.10)	(0.12)	(0.08)
Log GDP per Capita	0.00	-0.21^{**}	-0.16^{**}
	(0.05)	(0.09)	(0.07)
Log Natural Resource Rents	0.07^{**}	0.02	0.02
	(0.03)	(0.05)	(0.02)
DAC Aid	-0.04	0.04	-0.07
	(0.03)	(0.04)	(0.05)
Chinese Finance	0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.01)
IMF Program	0.15^{**}	-0.17	0.07
	(0.07)	(0.11)	(0.06)
UNSC Member	-0.15	0.29	0.11
	(0.15)	(0.19)	(0.09)
Voting with the US	1.39^{*}	-0.58	-0.50
	(0.71)	(0.99)	(0.43)

This table presents the results of four logistic regressions. In each regression, the dependent variable indicates whether a project was coded by the World Bank as belonging to the corresponding sector. All independent variables are lagged at $t-1$. Standard errors clustered by country and year. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

As discussed in the main text, the 11 official World Bank project sectors have important limitations: many projects have no sector labels, and even when they do, World Bank staff might face an incentive to mislabel extractive projects to appear more climate-friendly. In addition, the *Energy and Extractives* sector does not distinguish between non-renewables and renewables. For these reasons, the main models use topic prevalence as the outcome of interest. Still, additional models using World Bank project subsectors as the outcome lead to almost identical results, as Table F.1 shows.

In this table, the dependent variable *Sector: Extractives* takes the value of one for projects belonging to one of the following official World Bank subsectors: *Mining*, *Oil and Gas*, *Non-Renewable Energy Generation*, *Other Energy and Extractives*, and *Public Administration – Energy and Extractives*. The dependent variable *Sector: Climate and Renewables* takes the value of one for the following subsectors: *Renewable energy*, *Renewable Energy Biomass*, *Renewable Energy Geothermal*, *Renewable Energy Hydro*, *Renewable Energy Solar*, and *Renewable Energy Wind*. The dependent variable *Sector: Health* takes the value of one for the following subsectors: *Health*, *Health Facilities and Construction*, and *Public Administration – Health*. In the official World Bank classification, there is no separate category for the environmental sector.

The three logistic regressions in Table F.1 are substantively and statistically similar to the main models. After 2019, the absolute number of projects belonging to *Sector: Extractives* and *Sector: Climate and Renewables* decreased by 36 and 16 percent, respectively ($e^{-0.45} = 0.64$ in Model 1; $e^{-0.18} = 0.84$ in Model 2). Meanwhile, the absolute number of projects belonging to the health sector increased by 95 percent ($e^{0.67} = 1.95$, Model 3). As before, EITI members and countries with a large GDP share coming from resource rents tend to attract more extractive projects, though there is no equivalent effect for SIDS.

References

Eshima, Shusei, Kosuke Imai and Tomoya Sasaki. 2024. "Keyword-Assisted Topic Models." *American Journal of Political Science* 68(2):730–750.