Government Influence in Information Production in International Organizations

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Abstract

International organizations (IOs) provide information that shapes cooperation outcomes. Because of these downstream effects, the content of the information that IOs release matters. We argue that governments therefore seek to control IO information already at the stage of production inside IOs rather than only at the later stage when information gets disseminated. Drawing on original, non-public government comments data from a key climate science report of the Intergovernmental Panel on Climate Change (IPCC), we show that governments intervene in information production to preserve their national interests and that they do so strategically: governments request changes of text in exactly those paragraphs of the IPCC report that are most likely to have distributional effects at home. These findings emphasize variation in institutional rules of government involvement in upstream information production in IOs as an important scope condition for the credibility of IO information in international cooperation.

Word count: 9,566 words

Introduction

In global governance, information has important downstream consequences. Without it, international cooperation becomes protracted. Existing scholarship has shown that information, typically provided by international organizations (IOs) and their agencies, can help facilitate cooperation (Keohane, 1984; Milner, 1997; Abbott and Snidal, 1998). IOs help governments, citizens, businesses and other non-state actors mitigate information asymmetries: credible information about the underlying structure of a cooperation problem enables more effective governance (Mitchell, 2006) as does making states' actions and interests public. Equally, coordination and constraint can become incentive compatible through naming and shaming of government behavior (Hafner-Burton, 2008; Lebovic and Voeten, 2006; Tingley and Tomz, 2021), market responses (Simmons, 2000; Büthe and Milner, 2008; Gray, 2009; Morse, 2019) or domestic electoral pressure (Dai, 2005; Fang, 2008; Chaudoin, 2014). Despite differences in the exact function of IO information, the international institutions literature shares a broad focus on its downstream effects. That is, scholars have largely been interested in the mechanisms of how greater information, *once provided* by IOs, shapes international cooperation outcomes.

Complementing this work, in this paper we concentrate our attention on the stage *prior* to information provision. Specifically, we study the politics of *information production* in IOs. Information production refers to the gathering, collating, distilling, and processing of information that necessarily has to happen before an IO can release any information. Hence, information production is best conceptualized as the "upstream" process that generates the contents of the informational outputs that IOs provide, such as reports, data briefings, or press releases.

Our argument focuses on the politics of government influence in information production in IOs. We theorize that the extent to which states can and do shape the information that IOs produce is governed by both institutional rules and political motivations. This recognizes two central aspects. First, that information production will vary from one IO to the next as a function of institutional design. In IOs where governments are more involved in information production anyways, exercising control over the contents of this information will be easier. And second, that governments have strong incentives to seek control over information production to preserve national interests. We argue that this is the case because, if successful, shaping IO information outputs right at the source preempts many of the downstream effects that are usually attributed to IO information, such as constraining government actions (Mitchell, 1994; Dai, 2005; Fang, 2008; Chaudoin, 2014; Hollyer, Rosendorff, and Vreeland, 2015; Kelley and Simmons, 2019) or limiting bargaining space in international negotiations (Morrow, 1994; Hai, 2025). Influencing IO information production is therefore an attractive way for governments to shield national interests from downstream costs that would otherwise ensue from international cooperation.

We test our argument in the context of the Intergovernmental Panel on Climate Change (IPCC), the United Nations' (UN) primary body on climate science (de Pryck and Hulme, 2022; Hughes, 2024). The IPCC regularly publishes the most comprehensive assessments of what we know about climate physics, climate impacts, and mitigation options. These reports—and the "Summary for Policymakers" (SPM) as a condensed, high-level overview, in particular—set the scientific guardrails for any political response to the climate crisis. Mainly because of the expectation for governments to act in accordance with IPCC science, these reports have direct downstream consequences. They constrain bargaining spaces for government delegations in international climate negotiations under the United Nations Framework Convention on Climate Change (UNFCCC) (Hai, 2025).

Focusing on the production of one of the IPCC's latest and most influential SPM reports since the conclusion of the Paris Agreement (Falkner, 2016), we use original, non-public data in the form of written government comments from the SPM review stage. During this stage, which is similar to academic peer review, governments are invited to submit comments on a draft text of the report before its final version is negotiated line-by-line. Results from generalized linear regression models demonstrate that national interests correlate strongly with governments' attempts to influence the contents of IPCC reports at the sentence level. This is true for states whose economies are largely dependent on fossil fuels, but the pattern holds more broadly. Countries whose national interests are characterized in other ways, for example, by high levels of climate vulnerability, industrial manufacturing, agricultural production, or beef consumption all increase efforts to shape SPM text in their favor. Relying on keyword-assisted topic models (Eshima, Imai, and Sasaki, 2024) to validate hand-coded assignments of text sections to particular topics, we furthermore show that governments intervene strategically on exactly those parts of the IPCC text that have direct implications for national interests.

Our paper makes several contributions. First, it shows that governments seek control over upstream information production in IOs. They do so to minimize costly downstream effects on national interests from IO information. This finding highlights the under-theorized role of governments in IO information production in the international institutions literature—despite the widespread reliance of IOs on national governments' data, expertise, finances and staff as inputs into IO information production (Abbott and Snidal, 1998; Nielson and Tierney, 2003; Chwieroth, 2013; Clark and Dolan, 2021; Voeten, 2021; Clark and Zucker, 2024). As a result, IO information provision is probably less independent of government interests than what informational theories of international cooperation tend to assume (Martin and Simmons, 1998). Future research should therefore study how variation in institutional design empowers or firewalls government influence in information production and how it ultimately affects the credibility of IO information provision.

A second implication of our argument is that the power of IOs to facilitate international cooperation in highly technical areas may be limited. Issues such as cyber security, cryptocurrencies, antimicrobial resistance, or artificial intelligence all depend on specialist expertise and require input from national governments, thereby constraining the extent to which IOs can shield against government influence. Since many of these issues are novel topics, too, governments may attempt to strategically shape information production to endogenize the (informational) status quo for future bargaining on these matters (Kennard, 2023).

Third, we apply recent methodological advances in modeling the use of words (Eshima, Imai, and Sasaki, 2024) to study otherwise difficult-to-observe, "behind closed doors" information production processes in IOs. This contributes to the growing use of text-as-data approaches in international relations (e.g., Chaudoin, 2022; Thrall, 2025; Kennard, 2023).

Finally, our research speaks to the existing literature on distributional climate politics (Colgan, Green, and Hale, 2021; Aklin and Mildenberger, 2020; Bayer and Genovese, 2025). We build our argument from the same first principles that costs from ambitious climate policy will structure opposition to and support for international climate cooperation among the public, firms, and governments (Bechtel, Genovese, and Scheve, 2019; Genovese, 2019; Kennard, 2020; Cory, Lerner, and Osgood, 2021; Gaikwad, Genovese, and Tingley, 2022; Bayer, 2023). However, we extend this logic one step further and show that the same incentives that are rooted in the domestic political economy operate not only at the level of (downstream) international negotiations. They also apply to (upstream) information production processes that *precede* actual negotiations over cooperation outcomes. From a normative perspective, these results call for the more systematic study of the politics of information production in IOs and global governance.

International Cooperation and Knowledge about the State of the World

Without a clear sense about the underlying structure of a cooperation problem, coordinating state behavior is difficult. Governments find it hard to know what constitutes an adequate global governance response (Mitchell, 2006), and the politicization of uncertainty further complicates cooperation (Hai, 2025). While the cost associated with learning about the underlying problem structure is prohibitive for each country individually, international organizations can help facilitate cooperation because they benefit from economies of scale (Keohane, 1984; Milner, 1997; Koremenos, Lipson, and Snidal, 2001): pooling resources reduces the per-unit cost of information gathering and lowers the risk of free-riding (Abbott and Snidal, 1998; Mitchell, 1994). That is, IOs function as informational clearing houses. They collect, vet, and disseminate information. In doing so, they change what governments know about central aspects of a cooperation problem. This reduces the likelihood that government coordination breaks down over a lack of shared understanding of the true state of the world.

Many IOs, across virtually all issue areas of international cooperation, provide information about the state of the world as part of their core information outputs. The World Health Organization's *Weekly Epidemiological Reports*, for example, share information about disease outbreaks, including on COVID-19, cholera, and measles. The *Emissions Gap Report* by the United Nations Environment Programme provides annual updates about the link between climate action and projected global warming levels. And the International Monetary Fund's *World Economic Outlook* diagnoses the state of the world economy. In disseminating such information, IOs typically benefit from high levels of legitimacy (Abbott and Snidal, 1998; Dellmuth et al., 2021). Relative to information shared by individual governments, information provided by IOs is often seen as neutral, impartial, and more credible, primarily because information passes through a multilateral decision-making process that requires consensus and compromise by design (Mitchell, 1994; Fortna, 2003; Fang, 2008). As a result, most informational theories of international cooperation assume that IO information is largely free of government influence and exogenous to national interests (Martin and Simmons, 1998).

This notion of IOs as unbiased information providers, however, sits somewhat uncomfortably with two other observations from international institutions research. First, most IOs fulfil their information functions by relying considerably on knowledge, data, and expertise from member governments (Abbott and Snidal, 1998; Nielson and Tierney, 2003; Voeten, 2021). Governments, therefore, often control when, how, and to what extent national informational inputs feed into information production in IOs. Autocrats and populist leaders have been shown to throttle and restrict information flows to IOs strategically (Hollyer, Rosendorff, and Vreeland, 2018; Carnegie, Clark, and Zucker, 2024), strongly suggesting that the information IOs hold, at least in these cases, is a direct function of government control. Second, numerous studies document the mastery with which governments manage to shape IO decision-making outcomes in their favor through both formal and informal means (Stone, 2004; Dreher, Sturm, and Vreeland, 2015; Carter and Stone, 2015; Graham and Serdaru, 2020; Clark and Dolan, 2021; Pelc, 2014). Following the same logic, while turning our analytical focus from downstream decision-making outcomes to upstream information production in IOs, we advance an argument that roots government influence in IO information production in national interests and domestic distributive politics.

A Theory of Government Influence in IO Information Production

Our argument about government influence in IO information production comes in two parts. First, we argue that governments have strong incentives to *attempt* shaping the information IOs provide to mitigate costly downstream effects. Second, we claim that the way in which governments do so is a function of national interests.

Where IOs inform governments about the true state of the world, information typically concerns key structural aspects of the underlying problem and likely affects government behavior. This is the case because IO information legitimizes which government actions are politically justifiable. IO reports that are grounded in scientific evidence and multilaterally approved compel governments towards greater cooperation. Mutually agreed knowledge about the state of the world creates convergence in the set of appropriate state responses to global governance challenges (Haas, 1992*b*). For example, once scientists had discovered that chlorofluorocarbons cause ozone depletion, this knowledge about the physical nature of the problem prodded policymakers into action (Haas, 1992*a*; Benedick, 1998). Even for climate change, despite its larger scale and a more complex cooperation structure (Bernauer, 2013), scientific evidence from the IPCC's 1.5°C Special Report increased pressure on governments to ramp up climate action (e.g., Rowan, 2025).

IO information can therefore limit government actions if these were to contravene the scientific consensus that IO information is based on.[1] This makes states likelier to adopt policies they would, absent IO information, not have adopted. As these policies typically come with greater cooperation costs, one way for governments to try avoid these costs is by attempting to control the contents of IO information directly. Often, this is easier than protecting against downstream consequences.

Influence in information production allows governments to plant their national priorities and interests right at the source—i.e., when IO information is being created. In these cases, IO reports, as reference points for the "true" state of the world in downstream international negotiations, will embed the interests of governments that successfully influenced IO information production. Similar to the logic of far-sighted bargaining in international regimes (Kennard, 2023), where prior outcomes define the status quo of subsequent negotiations, government control in upstream IO information production endogenizes national interests in downstream information provision by IOs. Hence, interference is attractive because it creates the possibility for governments to control IO information production and create favorable bargaining positions in international negotiations down the line.

When governments do interfere with IO information production, we argue that they do so to preserve their national interests. This claim follows directly from combining the importance of downstream effects of IO information with existing research on the backlash against international cooperation from distributional losers (Colantone and Stanig, 2018; Broz, Frieden, and Weymouth, 2021; Colgan, Green, and Hale, 2021; Ballard-Rosa et al., 2021). On the one hand, better knowledge about the state of the world often justifies greater cooperation collectively and pushes governments in that direction. On the other hand, policymakers fear the pushback from voters and industries that loath cooperation for its associated costs. With the rise of populism in many democracies, such distributional pressures receive increased attention (De Vries, Hobolt, and

[1] Our focus in this paper is on IO-provided information about the state of the world and the constraints for government behavior that follow. Others have shown that IO-provided information about government behavior itself (instead of the state of the world) is critical for states to overcome commitment problems that otherwise undermine international cooperation and compliance (Simmons, 2000; Dai, 2005; Büthe and Milner, 2008; Fang, 2008; Gray, 2009).

Walter, 2021). From Brexit to the energy transition, mainstream incumbents struggle with populist leaders' electoral successes (Colantone and Stanig, 2018; Colantone et al., 2024; Voeten, 2024; Gazmararian, 2024).

In such a competitive political environment, deeper international cooperation is a difficult sell for leaders, also because populists understand to portray IOs as elitist and anti-nativist (Copelovitch and Pevehouse, 2019; Brutger and Clark, 2023). Ambitious climate action which threatens job losses in carbon-intensive sectors at home is equally unpopular with voters as is pushing free trade when this drives domestic import-competing firms out of business. Faced with such tensions, we argue that governments can reduce pressures to even having to confront distributional effects from deeper cooperation in the first place by seeking control over upstream IO information production.

Protecting salient domestic interests through information production becomes possible only because scientific evidence, which we assume IO information relies on, is multifaceted and complex; it also needs to be translated into what it means for policy applications. Governments are therefore able to interpret and portray the *same* scientific evidence differently and in ways that conform with national priorities (Allan, 2017). Practically speaking, then, there often is plenty of room in information production for governments to try and push their own interpretations of scientific evidence. Such attempts are not necessarily ill-intentioned. Legitimate reasons for views to differ exist, for example, in cases where global IO reports lack geographical nuance, thereby disadvantaging some countries or regions over others. In other cases, governments will indeed seek control in IO information production purely to manipulate and obstruct.

No matter whether motivations are good or bad—and our argument is deliberately agnostic here—we argue that governments attempt to influence upstream information production in IOs to preserve national interests and to control the downstream effects of information provision by IOs. But, how do governments use IO information production to preserve national interests, in practice? They can do so either by creating rents or by deflecting harm. Without doubt, pushing an explicit reference to a national drug maker's product into a World Health Organization report will create immediate rents for this company. Equally, governments managing for UN climate reports to encourage the use of carbon dioxide removal technologies will throw a lifeline to carbon intensive industries, shielding them from fossil fuel phaseout. In either case, the reliance of IOs on inputs from governments ensures their access to information production.

While the possibility for governments to exercise influence in information production is clearly greatest when institutional rules are permissive and invite, or even require, government participation in these processes, governments are likely to find alternative ways to obtain access through their direct and indirect control of data, expertise, and resources (Abbott and Snidal, 1998; Nielson and Tierney, 2003; Chwieroth, 2013; Clark and Dolan, 2021; Voeten, 2021; Clark and Zucker, 2024). Even for well-staffed, well-endowed IOs like the World Bank, several countries, including China, managed to interfere with the information production of the Bank's *Doing Business Report* (World Bank, 2021). Institutional capacity alone is hence no guarantee to effectively limit government influence in IO information production.

Background on the IPCC

We test our argument's key observable implication that *governments interfere with IO information production to preserve national interests* in the case of a major IPCC climate report, where rich variation in national interests allows for a nuanced empirical analysis of government influence in upstream IO information production.

Founded by the World Meteorological Organization and the United Nations Environment Programme in 1988, the Intergovernmental Panel on Climate Change (IPCC) serves as the UN system's main body on climate science and has become one of the most prominent intergovernmental science organizations today. As an IO with a permanent secretariat in Geneva, its task is to assess and summarize existing knowledge rather than conduct its own research. The IPCC delivers on this mandate across its three work streams on the physical science basis (Working Group I), climate impacts (Working Group II), and mitigation options (Working Group III), each of which publishes a set of reports at the end of an assessment cycle of 5–7 years. These IPCC products come in the form of an underlying report of more than 1,000 pages, a Technical Summary, and a Summary for Policymakers (SPM), which distills central messages into headline statements for political decision makers.[2] These information outputs, particularly the SPM, matter because they feed scientific evidence into annual UNFCCC meetings (Hai, 2025), where negotiated outcomes create downstream policy effects.

The IPCC, at its core, therefore functions as an information provider to its 195 member governments. Like many other IOs, it disseminates information about the state of the world (Abbott and Snidal, 1998; Martin and Simmons, 1998). It thereby structures governments' policy responses to climate change through scientific knowledge and information (Hughes, 2024). On a practical level, the IPCC relies on inputs from member governments for the production of its reports in several ways. Governments nominate report authors and approve the outline of all IPCC reports. For the SPM as the main policy-facing output, governments additionally comment on a draft version of the SPM before the revised text is approved line-by-line during a week-long intergovernmental plenary meeting.

The IPCC's institutional rules deliberately permit government participation. They were designed consciously in such a way to facilitate ownership of and shared responsibility for any of the IPCC-produced reports among member governments (de Pryck and Hulme, 2022). Although well-intentioned, an institutional design like this—as premised by our theory—creates opportunities for governments to shape the contents of IPCC reports and is hence an ideal case for testing our argument empirically. We focus our data analysis on the *review stage* of the SPM writing process as a key point in the report's production cycle where governments can directly shape the language

[2] During a typical assessment cycle, the IPCC publishes at least these three documents *for each* of its three Working Groups, plus an overarching Synthesis Report. In addition, it often also publishes Special Reports that are commissioned, upon intergovernmental approval, at the start of an assessment cycle. All IPCC publications are available at https://www.ipcc.ch/reports/.

used in the SPM. They do so by submitting written, non-public comments to the report's authors requesting edits, additions, or deletions to the text, which authors can accept or reject. The SPM text typically changes considerably as a result of government comments, for example, boosting the word count of an already 43 pages-long document by roughly 25% in our case. This makes the review stage an integral part of an SPM's life-cycle.[3]

Government review, as an instrument to solicit feedback and expertise from member governments, is common across many IOs yet the details and purpose of the review process vary. The International Monetary Fund (IMF), for example, includes government comments into its Country Reports to contextualize its analysis with local knowledge (Lombardi and Woods, 2008). The Nuclear Technology Review and the Nuclear Safety Review, both global reports published by the International Atomic Energy Agency (IAEA), are written in light of comments by IAEA member states. Ranging from the World Health Organization's annual World Health Report to the World Trade Organization's dispute settlement mechanism, opportunities for governments to seek influence in IO information production span across a wide set of issue areas in global governance, including the environment, trade, energy, corruption, development, and human rights (Pelc, 2014). The IPCC is therefore hardly an outlier when it comes to formalizing rules for government influence in the writing of its flagship reports and SPMs.

IPCC member governments make ample use of the SPM review process, validating our priors that the contents of these reports matters. In this article, we study the latest Working Group III Summary for Policymakers, published in April 2022, which is the first major SPM on climate mitigation policy after states had agreed ambitious climate targets under the Paris Agreement. A total of 4,954 comments were submitted by 43 government delegations on the initial SPM draft—or,

[3] The SPM of Working Group III of the latest Sixth Assessment Report (April 2022), which we study below, saw 17 pages added as track changes, increasing the SPM's total word count from 17,359 words to 22,212 words. We also calculate fairly low measures of similarity between the text versions before and after review comments: a Levenshtein similarity of 0.51 and cosine similarity of 0.75 (based on term frequency-inverse document frequency, TF-IDF). This offers descriptive evidence that review comments changed the text and language in the SPM substantially.

roughly 115 comments per page, on average. Given that states exert such levels of effort to shape the language in these reports, they must clearly see value in trying to exercise control over information production in the IPCC. We use these data to demonstrate that governments comment on international climate policy as a function of national interests more broadly and on distributionally relevant policy options in particular.

Empirical Patterns in Government Efforts to Shape SPM Text

For our empirical analysis, we rely on the complete set of non-public comments that governments submitted in response to the Working Group III (WGIII) SPM draft text for the IPCC's Sixth Assessment Report (AR6). These comments, which are available to report authors, IPCC member governments, and authorized researchers (like us) from accredited observer organizations, offer a detailed, sentence-level account of government efforts to shape IO information production. They are a unique data source because, compared to other IOs where governments influence information production behind closed doors and without leaving a "trace," attempts to change SPM text during the IPCC's review stage are documented in writing. Access to these written comments that are outside the public domain allows us to directly measure otherwise difficult-to-observe efforts by governments to influence information production in IOs.

Below, we use these data to provide two sets of evidence in support of our argument. First, we show that governments from oil-producing countries are more active in trying to shape SPM text. Second, we demonstrate that national interests *beyond oil* structure government attempts to shape information production in a similar way. Indeed, dependence on other climate-forcing assets or high levels of climate vulnerability as alternative markers for national interests also translate into government activity to shape IPCC outputs. Conforming to our expectations, governments are furthermore strategic in their commenting behavior: they intervene specifically on those *topics* in the SPM text that have relevant implications for their corresponding national interests and policy priorities at home. We exemplify this in the context of policy options related to carbon capture and storage (CCS) technologies and agriculture, forestry, and land use (AFOLU) emissions. We offer combined evidence for our main expectation that governments will intervene in IO information production as a function of national interests that are rooted in concerns over the domestic distributive consequences of greater cooperation on climate change.

Since the 4,954 written comments are intended to effect changes to the SPM text, they are a good operationalization of efforts to influence information production in the IPCC by the 43 government delegations that submit them. Our effective sample size reduces to 4,347 comments from 42 governments after excluding 381 comments by the European Union and another 226 comments which either referred to the whole SPM document or which, even after careful checks, could not be attributed to any specific part of the text.[4] The latter selection is necessary for our research design.

Excluding the introduction (section A) which primarily contextualizes and outlines the report, the SPM draft for WGIII in AR6 comprises 40 of what we call "parts of text" (POTs). We define these POTs as self-contained textual, visual (i.e., figures), or numerical (i.e., tables) blocks of information on specific aspects of mitigation policies. They follow quite naturally from the SPM's hierarchical structure, which is divided into headline statements—referenced as 'B.1', 'B.2', ... 'C.1', 'C.2', and so forth—and lower-order paragraphs that provide scientific evidence to support headline statement claims—e.g., 'B.1.1', 'B.1.2', and 'B.1.3' back up statement 'B.1'.[5] We link submitted comments to specific POTs based on page and line information that a comment refers to in the text. Figure 1 illustrates such a mapping for two example comments, ID 13948 from Norway (referring to line 11 on page 23) and ID 13570 from Saint Lucia (referring to lines 7-11 on page 23), both assigned to POT 'C.5' (lines 7-11 on page 23) on emission-reduction strategies in industrial processes. Being able to link government comments to POTs strengthens our empirical

[4] As part of the data cleaning process, our research team manually checked that *all* submitted comments map to SPM text correctly and meaningfully.

[5] As figures and tables attract substantial attention by policymakers and hence also receive a large number of government comments, we treat each figure and table as a separate POT rather than assigning them to the paragraph in which they appear. The SPM draft we analyze has 11 figures and one table.

strategy. First, it allows us to include POT-level fixed effects in our regression models. Second, it allows for a separate, topic-level analysis as different POTs relate to different topics.

C.5 Effective emission reductions from industry entail coordinated action throughout value chains to promote demand management, energy and materials efficiency, and circular material flows. Progressing towards net zero GHG emissions from industry also necessitates the adoption of new primary processes using low to zero GHG electricity, fuels, hydrogen and carbon feedstocks, and employing CCS for remaining CO2 (*high confidence*). {11.2, 11.3, 11.4, Box TS.4}

Government of Saint Lucia: This headline statement requires information, at least in a footnote, pointing to the potential caveats of employing CCS for remaining CO2.

Government of Norway: Please delete "...for remaining CO2".

FIGURE 1: Illustration of mapping government comments to POT in SPM text. We locate example comments with ID 13948 from Norway and ID 13570 from Saint Lucia to POT 'C.5' based on page and line information that each government provides together with any request to change SPM draft text. Full set of comments: $N = 4{,}347$.

Figure 2 shows the number of submitted comments for the 25 governments that comment the most, together with the number of comments submitted on POTs that focus specifically on CCS technology (yellow) and AFOLU emissions (green)—the two topics we will return to in our second analysis below. These data provide initial evidence that national interests tied to oil production, be it through direct exploration or through being home to the headquarters of large oil multinationals, matter for the total number of submitted comments, as can be inferred from countries like the US, France, the UK, Saudi Arabia and Norway ranking high on the list. National interests are, however, multidimensional and hence not exclusively linked to oil. In the case of small island states like St. Kitts & Nevis, Jamaica, and St. Lucia, it is the existential threat that climate change poses to these countries' survival, which aligns commenting heavily during the SPM review with their national interests. We study such multidimensional interests in our two empirical analyses.

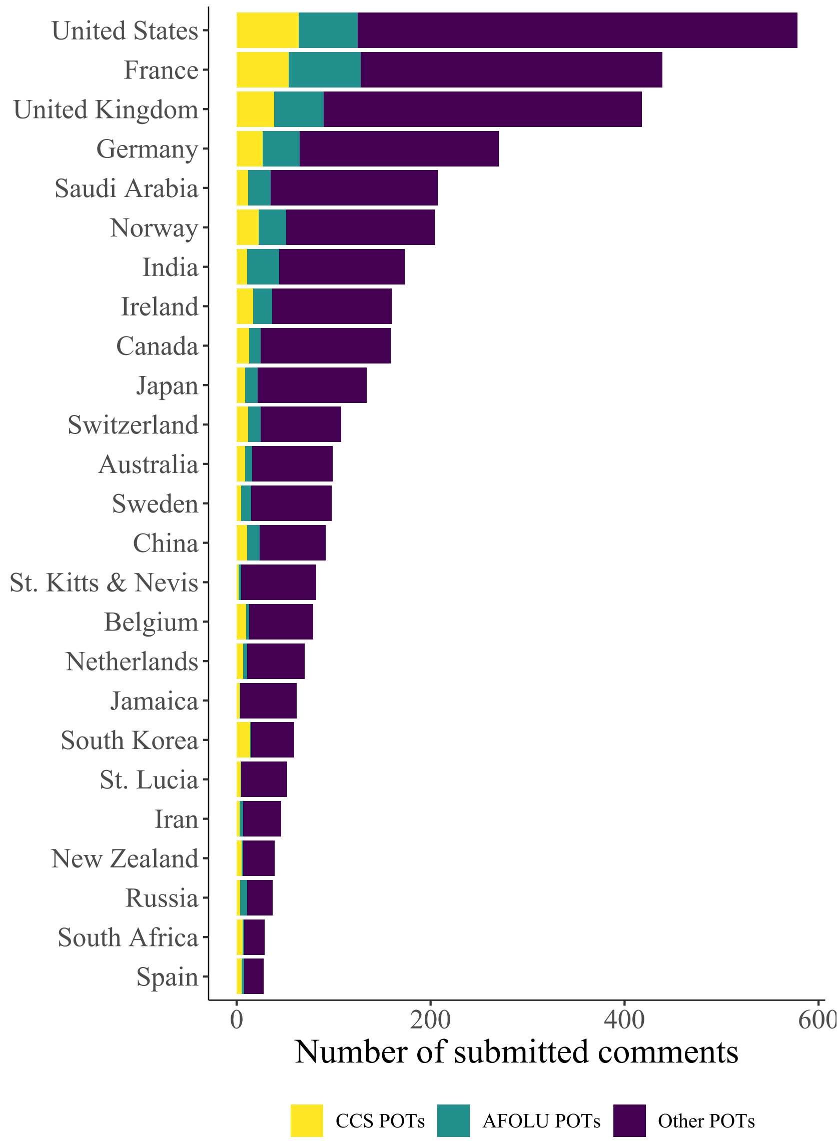

FIGURE 2: Number of government comments by country and topic for WGIII SPM draft text. We plot the top-25 countries with the largest number of overall comments.

Analysis 1: Oil Capital and Government Influence in Report Production

Our first analysis shows that the intensity with which governments attempt to shape IPCC-produced information in SPM reports increases with national interests tied to oil production. We do so by conceptualizing a country's national interest through its reliance on oil as a key climate forcing asset and operationalize it as country-level per capita measures of (logged) oil capital. This "topline" indicator recognizes the structural embeddedness of oil in advanced economies. Because of the outsized influence of fossil fuel interests in climate politics (e.g., Stokes, 2020; Mildenberger, 2020; Colgan, Green, and Hale, 2021; Cory, Lerner, and Osgood, 2021), we expect a country's oil dependence to fundamentally shape how actively a government intervenes in IPCC report production.

To measure the intensive margin of governments' efforts to influence IPCC text, we count the number of comments submitted by each government on each of the 40 uniquely identified parts of text (POT). On average, member governments submit about four comments on any given POT, but the distribution is skewed as a median of just one comment per government-POT pair indicates (Table A.3).

Our analysis rests on a selection on observables design. We include several control variables[6] to minimize confounding in the estimated relationship between national interest and government efforts to shape information production in the IPCC. We add covariates on CO_2 emissions and natural resource rents as more polluting and highly resource-dependent states have strong incentives to shape the contents of IPCC reports. The inclusion of controls for GDP (in constant prices) and GDP growth (in percent) hedges against concerns that richer economies are more reliant on fossil fuels to sustain their economy, and its growth, and are therefore more likely to intervene in SPM text production. We also minimize the risk of spurious correlation arising from cross-country differences in research power and variation in countries' familiarity with and capacity to engage in IPCC processes: we control for a country's scientific strength with data on the number of academic articles published in natural science journals, as measured by the *Nature* Research Leaders Index, and the size of government delegations during the IPCC WGIII SPM approval plenary to proxy for national "buy-in" into the IPCC. As both the SPM and review comments are written in English, we add a binary indicator to our models that records whether English is a country's official language

[6] We describe all variables and their sources in Tables A.1 and A.2.

or not. We average covariates over the years from 2015 to 2021, which mark the start dates of the IPCC's assessment cycle and the SPM review, respectively, to smoothen over-time trends and to ensure covariates are measured pre-treatment.

We estimate Poisson regression models of our count variables. POT-level fixed effects remove any variation across POTs from, for example, differences in topic, length, technicality, or imprecision in the report text. These models explain government attempts to shape SPM contents—through submitting comments to the IPCC—from average within-POT variation as a function of national interest (measured as oil capital) and covariates.

We expect a positive association between oil capital and the number of submitted comments, when holding constant POT-specific features and covariates. In the logic of our argument, this means that governments with greater national interest in the downstream effects of IPCC reports—for example, think of IPCC information intimating the need for substantial cuts to global oil production—will submit a greater number of comments during the SPM review stage. Identification of this estimate rests on the conditional independence assumption relative to only country-level features because any text-level confounding is accounted for through POT-level fixed effects. A sensitivity analysis (Cinelli and Hazlett, 2020) offers credible evidence that this identifying assumption very plausibly holds.

Results: Count Models

Table 1 presents several models, ranging from a parsimonious specification to avoid suppression effects (Lenz and Sahn, 2021) to models with more complete sets of control variables. Across all of them, we find that governments of countries with higher levels of oil capital submit a greater number of comments on the average POT of the draft SPM. In estimating these effects, which are all statistically significant and increasing in size when relevant controls are added, POT-level fixed effects completely absorb any confounding due to the very topic discussed in a given part of text.

The estimated effects are substantively large. For model (1), which produces the smallest point

Table 1: Poisson regression results for the number of government-submitted comments during SPM review

	Dependent variable: Comments (count)			
	(1)	(2)	(3)	(4)
Oil capital per capita (log)	0.266**	0.398***	0.351**	0.379*
	(0.082)	(0.069)	(0.125)	(0.170)
CO_2 emissions (kg)		-1.427**	-1.684*	-1.053
		(0.459)	(0.811)	(0.751)
GDP (trillions)			0.120***	-0.341***
			(0.011)	(0.096)
GDP growth (%)			-0.085	-0.012
			(0.092)	(0.094)
Natural resources (GDP %)			0.027	0.024
			(0.044)	(0.045)
Nature research leaders (count)				0.315***
				(0.075)
WGIII AR6 delegation size (count)				0.013
				(0.016)
Anglophone country (binary)				-0.028
				(0.253)
POT-FE	✓	✓	✓	✓
Clustered SE	✓	✓	✓	✓
Num.Obs.	1640	1640	1640	1640
R2	0.140	0.205	0.385	0.432
R2 Adj.	0.136	0.200	0.381	0.427

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note: Dyadic dataset of 42 countries × 40 parts of text (POTs). All models are Poisson regressions with the number of government-submitted comments for each POT as outcome variable. Variables are averaged over 2015-2021 period. POT-level fixed effects are included in all models. Standard errors are clustered at the country-level and POT-level.

estimate across all our specifications, an increase in oil capital per capita of one standard deviation (+1.18) over its mean (0.74) increases the number of submitted comments on an average POT by 1.24 [0.33, 2.15], or roughly a third of the mean. This positive relationship holds for the full range of the oil capital variable, as shown in Figure 3. There, we plot predicted counts together with the 95% confidence intervals to show that the number of submitted comments is strictly and non-monotonically increasing in countries' reliance on oil production. For instance, a country like Spain with virtually no oil capital (US$30 per capita) is predicted to submit 3.25 [3.23, 3.27] comments per POT, while Denmark, whose oil capital of US$2,950 per capita sits at the middle of the empirical distribution (shown as the dashed line in the figure), is expected to submit 4.64 [3.72, 5.79] comments. These numbers double and triple at the far end of the distribution for oil-rich nations like Norway (US$38,470 per capita) and Saudi Arabia (US$174,300 per capita), which are expected to comment 8.56 [4.73, 15.51] and 12.73 [5.52, 29.34] times on any given POT, respectively.

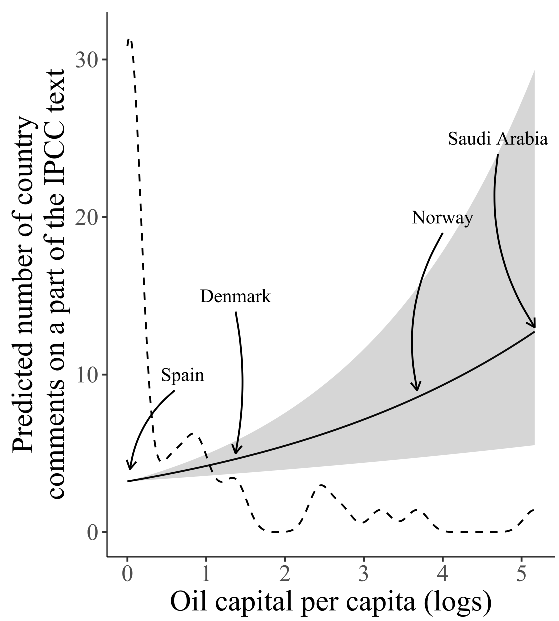

FIGURE 3: Number of submitted review comments by governments as a function of their oil capital per capita. Predicted counts are shown as the black line with the 95% confidence interval in gray, based on model (1) from Table 1. The dashed line shows the empirical distribution of the logged oil capital per capita variable. Four countries are highlighted as examples.

While our research design prevents a strict causal interpretation of the estimated effects, sensitivity analysis helps us demonstrate the internal validity of our results. Following Cinelli and Hazlett (2020), we find that even in the presence of a large unobserved confounder that was ten times as strong as the most predictive variables in a benchmark specification, the coefficient of oil capital per capita would still be positive and strong.[7] Figure 4 (left panel) shows that for the three most predictive covariates from model (4) above, the effect of oil capital gets estimated as 0.252, 0.359, and 0.342 (relative to a point estimate of 0.379) for confounders that are ten times as strong as the natural resources availability variable, the GDP variable, and the *Nature* research leader index variable, respectively. Hypothesizing even such extreme forms of unobserved confounding, the obtained point estimates would therefore remain substantively large (comparable in size to the reported effect of 0.266 from model (1), which we used to illustrate substantive effects in Figure 3); they would also largely retain statistical significance (except for a confounder ten times as strong as the natural resources variable). This analysis lends credibility to our main inference that national interest tied to oil production drives the intensity of governments' attempts to influence SPM text as our identifying conditional independence assumption very plausibly holds.

[7] The predictive 'strength' of a variable is defined as the explanatory power between treatment and outcome variables in terms of the partial R^2.

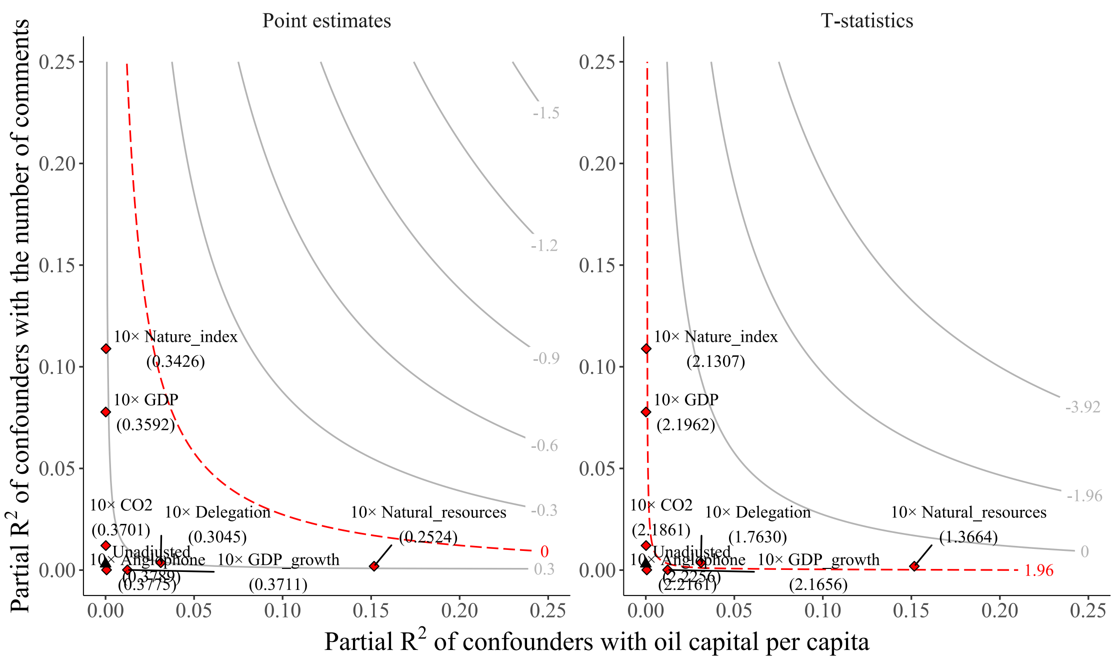

FIGURE 4: Results of sensitivity analysis. Following Cinelli and Hazlett (2020), we show that the effect of oil capital per capita on the number of government-submitted comments on SPM parts of text remains positive and significant even in the presence of a large unobserved confounder. Results for point estimates (left panel) and t-statistics (right panel) are shown. Analysis is based on model (4) in Table 1 as benchmark specification.

Analysis 2: Non-Oil National Interests and Topic-Specific Government Influence in Report Production

So far, we have shown that governments' attempts to shape the contents of the average SPM POT intensify as their dependence on oil production (measured as oil capital per capita) increases. This result is perhaps unsurprising given the central role that oil plays in climate politics. As a next step, we now ask whether other structural features linked to climate change, such as countries' climate vulnerability or their reliance on other climate forcing assets that are not about oil, have similar effects on efforts to interfere in IPCC report production. This also prompts the question of whether governments' attempts to change SPM text are independent of a paragraph's topic or are tailored to specific sections of text.

Our second analysis indeed shows that our argument applies to a much broader set of national interest considerations that are unrelated to oil. These additional tests of our theory allow us to study commenting behavior of governments that are less dependent on oil, but whose national interests are nonetheless tightly linked to climate policy through other channels. Since we expect these governments to submit an overall smaller number of total comments compared to those governments primarily driven by oil interests, we use a binary (instead of a count) outcome measure in our models below to record whether a government has commented at least once (=1) or not at all (=0) on each of the 40 individual POTs. We hence model the extensive margin of government influence across the full SPM text.

National interest is multi-faceted and varies across contexts: what is a key political priority in one country does not matter elsewhere. This is why countries will assess the downstream effects of IPCC reports in light of their own national interests: states with a strong manufacturing base will worry about evidence in the SPM that can be read as necessitating faster industrial decarbonization; other states, especially the ones hit hard by climate impacts, will, in turn, worry about language in the SPM that lacks urgency to take collective climate action.

We respond to this variation in national interests by relying on four separate measures that capture key dimensions of structural features that determine national interests in the context of international climate politics. First, we operationalize national interest through climate vulnerability, which we code as a binary variable based on whether a country is classified as a Small Island Developing State (SIDS) according to the UN. For these 39 highly climate vulnerable countries—including Jamaica, Fiji, St. Lucia, and St. Kitts & Nevis—global warming poses an existential threat. This makes their national interests almost synonymous with ambitious, internationally coordinated climate action.

The other three measures focus on different types of "climate forcing assets" (Colgan, Green, and Hale, 2021, 587) that are known to shape states' national interests on climate cooperation (Genovese, 2019). Specifically, we use separate data on a country's value added to its economic output from two particular sectors, i.e., from industrial production—which includes manufacturing, mining, construction, and electricity production as core, carbon-intensive activities—and from agriculture, forestry, and fishing. Industrial and land use emissions, as captured by these two variables, are both large contributors to a country's structural carbon footprint. Our fourth measure on the economic value of domestic bovine meat consumption approximates country-level variation in carbon-intensive beef diets. This varied set of measures helps us empirically characterize the multidimensional nature of countries' national interests and how they relate to climate politics and IPCC information production. We logarithmize all our variables (except for the SIDS dummy).

Our argument makes us expect that governments *target* their intervention efforts on exactly those POTs of the IPCC report that matter the most for national interests in terms of distributional downstream effects. The observable implication of this is that government influence in text production is therefore not random, but is instead tailored to precisely those sections and paragraphs that discuss topics that are salient to interests at home.

We focus on two key topics in climate mitigation policy (Bayer et al., 2025): carbon capture and storage (CCS) and agriculture, forestry, and other land use (AFOLU) emissions. For both CCS and AFOLU, we identify POTs from across the SPM that are relevant to these two topics.[8] Based on a qualitative assessment from reading the SPM, we assign POTs B.4, C.5, and C.11 to CCS and POTs C.6, C.9, D.1, and D.2 to AFOLU,[9] but results are robust to using a semi-supervised topic model for classifying topics (Eshima, Imai, and Sasaki, 2024) as an alternative to manually mapping topics to POTs (Appendix B.6).

CCS is an ideal topic for our analysis because both advanced economies and climate vulnerable countries associate strong national interests with it, albeit for different reasons (Anderson and

[8] We define both topics in broad terms. Our CCS topic includes references to related technologies like carbon dioxide removal (CDR), carbon capture and utilization (CCU), bioenergy with CCS (BECCS) and direct air carbon capture and storage (DACCS). The AFOLU topic includes issues of land use, land use change, and forestry (LULUCF).

[9] POTs that refer to CCS received 391 comments (9% of total), AFOLU POTs received 448 comments (10% of total) (Figure A.1). This ensures that there is sufficient empirical support for conditioning on these two topics in our interaction models.

Peters, 2016). As a technology to capture and permanently store CO_2 underground, countries with large industrial sectors see CCS as a way to reduce their impact on the world's climate, while being able to continue their carbon-intensive operations. In contrast, climate vulnerable countries and small island developing states (SIDS), in particular, worry that CCS deters deep decarbonization, slows climate action, and risks runaway climate change. The way CCS is described in IPCC reports and what scientific evidence about it is presented hence matters for national interests in SIDS and industrialized economies alike. We therefore expect governments from both types of countries to seek influence in text production of specifically those POTs that talk about CCS.

Our second topic refers to sections in the SPM about agriculture, forestry, and land use (AFOLU) emissions. Especially for large forest nations, such as Brazil and Indonesia, emissions from these sources often account for a third of their terrestrial greenhouse gas (GHG) emissions or more. Scientific evidence on forest governance and land use practices from IPCC reports will therefore matter greatly for national interests in these states. Standing forests serve as carbon sinks, but pressures to convert land for agricultural use for high value crop and meat production by agribusiness conglomerates will lead governments dependent on these interests to intervene on SPM sections on this very topic.

To empirically test our expectation that government interventions are topic-specific, we estimate a series of logistic regressions that model attempted government influence as an interaction (and their constituent terms) of national interest and topic-specific dummy variables for CCS and AFOLU, which are 1 for the above identified POTs and zero otherwise. Since CCS matters for SIDS and industrialized states, and AFOLU matters for countries with large agricultural production and high levels of meat consumption, we interact our measures of national interest and topic dummies accordingly. We include the same controls as in the previous analysis and prefer model specifications without POT-level fixed effects as topic dummies are POT-invariant. We demonstrate that parameter estimates are almost identical when these fixed effects are added.

Results: Topic-Specific Interaction Models

Our second set of results demonstrates that governments seek influence in IPCC report production for many forms of national interest other than oil. We show, in particular, that governments comment *strategically* on topics that matter for their national interests. Table 2 presents evidence from a total of 12 models: three each for the four different measures of national interest, operationalized as SIDS membership (models 1–3), value added from industrial production (models 4–6), value added from agricultural production (models 7–9), and beef consumption (models 10–12). Models 1–6 include interactions with the CCS topic dummy, models 7–12 include interactions with the AFOLU topic dummy, and specifications differ by whether control variables and POT-level fixed effects are included.

Table 2: Logistic regression results for interaction models of national interest and topic-specific parts of text

	Dependent variable: Comments (binary)											
	SIDS[1]			Industry[2]			Agriculture[3]			Meat[4]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
National interest	-0.011	0.555	0.581	2.392	5.244*	5.513*	2.525	2.607	2.737	0.280	-0.116	-0.123
	(0.571)	(1.160)	(1.219)	(1.491)	(2.098)	(2.164)	(2.151)	(6.409)	(6.760)	(0.236)	(0.297)	(0.313)
National interest × Topic: CCS	0.744***	0.883***	0.934***	4.426**	3.640***	3.933***						
	(0.111)	(0.259)	(0.264)	(1.631)	(0.813)	(0.948)						
National interest × Topic: AFOLU							15.916*	10.770***	11.321**	0.305***	0.358**	0.379**
							(7.869)	(2.732)	(3.524)	(0.019)	(0.111)	(0.142)
Topic: CCS	0.236	0.276		-0.181	-0.083							
	(0.242)	(0.298)		(0.250)	(0.308)							
Topic: AFOLU							-0.433*	-0.378		-0.409*	-0.456*	
							(0.211)	(0.250)		(0.185)	(0.229)	
Controls		✓	✓		✓	✓		✓	✓		✓	✓
POT-FE			✓			✓			✓			✓
Clustered SE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Num.Obs.	1680	1640	1640	1680	1640	1640	1680	1640	1640	1640	1640	1640
R2	0.002	0.127	0.161	0.068	0.139	0.173	0.017	0.127	0.162	0.018	0.124	0.158
R2 Adj.	-0.001	0.118	0.117	0.065	0.130	0.130	0.014	0.118	0.118	0.016	0.115	0.115

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001
[1]National interest measure: Membership in the "Small Islands Developing States" (binary). Source: UN
[2]National interest measure: Industry, value added (trillions of 2015 US $, logs). Source: WDI data
[3]National interest measure: Agriculture, forestry, and fishing, value added (trillions of 2015 US $, logs). Source: WDI data
[4]National interest measure: Bovine meat consumption, value (billions of 2014–2016 international $, logs). Source: FAO data
Note: Dyadic dataset of 42 countries × 40 parts of text (POTs). All models are logistic regressions a binary indidcator of whether a government submitted at least one comment (= 1) or not (= 0) for each POT as outcome variable. Variables are averaged over 2015-2021 period. Standard errors are clustered at the country-level and POT-level. 'CCS' stands for 'carbon capture and storage' technology; 'AFOLU' stands for 'agriculture, forestry, and other land use'.

Conforming to our expectations, the likelihood that governments attempt to shape SPM text increases only in cases where national interests are "activated" by a particular topic. Statistically, this is captured by the positive and significant interaction term across all models, while the constituent term of national interest by itself (except for models 5 and 6) is estimated inconsistently and tends to be substantively small. These results offer strong evidence for our interpretation that governments are indeed strategic in their efforts. They do not use a scatter-gun approach of seeking influence on all sections of text equally. Instead, they submit comments on precisely those POTs that cover topics with relevant distributional downstream effects for their national interests.

We facilitate the substantive interpretation of the estimated interactions by computing marginal effects from models 1, 4, 7, and 10 in Table 2. To do so, we increase all our continuous measures of national interest by one standard deviation above the mean (+1 SD) and use a binary SIDS *vs* non-SIDS contrast for the SIDS variable. Figure 5 shows marginal effects separately for whether POTs cover CCS (left panels)/ AFOLU (right panels) as main topic or not. For all four different measures, we find that marginal effects of national interest on governments' attempts to shape IPCC text increase, but only for sections on CCS and AFOLU. In contrast, marginal effects for all other sections are flat.

Effect sizes are generally large. For national interests tied to industrial and agricultural production, we see increases in the probability to comment by about 40 percentage points on POTs covering relevant topics (i.e., CCS in the case of industrial production and AFOLU in the case of agricultural production). Interests operationalized through SIDS status and beef consumption result in smaller marginal effects of 15 percentage point shifts in predicted probabilities for governments to comment on associated CCS and AFOLU POTs. The effects of our binary SIDS measure as a proxy for climate vulnerability are the only ones that are not estimated tightly enough to pass standard tests of statistical significance—plausibly either because of increased variance in the measure itself or because SIDS tend to coordinate their contributions to IPCC proceedings through select spokescountries. In sum, we find strong empirical support for our central claim that governments comment strategically on SPM text and that government influence in IPCC information production is topic-specific.

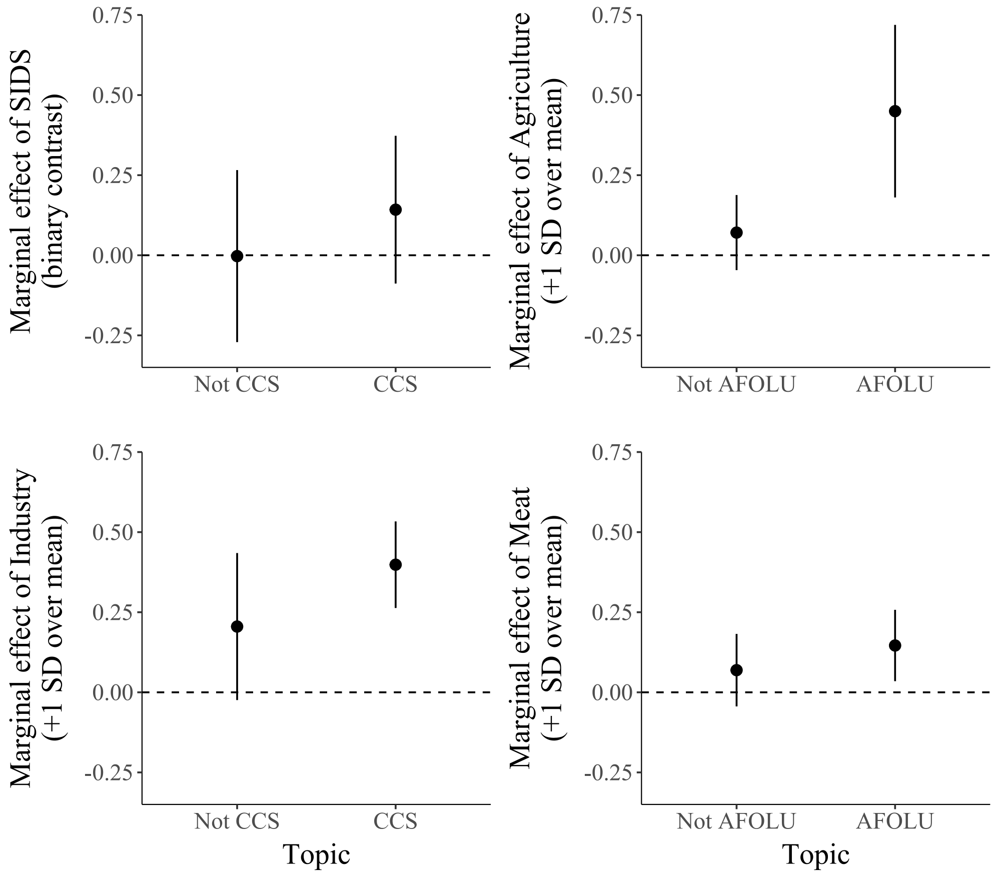

FIGURE 5: Marginal effect of national interest on probability to submit comments on SPM parts of text. Plots show marginal effects and 95% confidence intervals from models (1), (4), (7), and (10) in Table 2 when changing all four measures of national interest from the mean to one standard deviation (+1 SD) above the mean (except for SIDS dummy). Plots visualize contrasts for POTs focusing on CCS or not (left panels) and POTs focusing on AFOLU or not (right panels). 'CCS' stands for 'carbon capture and storage' technology; 'AFOLU' stands for 'agriculture, forestry, and other land use'.

Robustness

In the appendix, we demonstrate the robustness of our findings. We begin by showing that our main results do neither depend on the decision to log-transform our national interest measures (Appendix B.2) nor on whether we model our dependent variables with ordinary least squares (OLS) rather than with non-linear link functions for count and binary outcomes (Appendix B.3). Appendix B.4 affirms that oil capital matters primarily for the intensity with which governments engage in the review process, that is, for the number of comments they submit to the IPCC, rather than whether they comment at all.

We also conduct placebo tests to validate our claim that oil capital structures attempts to influence IPCC report production in general and is hence *not* conditional on topic, whereas other forms of national interest only have topic-specific effects (Appendix B.5). In our main analysis, we identify POTs that relate to CCS and AFOLU through qualitative coding of the contents of POTs, yet results are very similar when we classify these topics based on information about the expected main topic or topic proportions from a semi-supervised topic model (Eshima, Imai, and Sasaki, 2024) (Appendix B.6). We finally also use regression-implied weights (Aronow and Samii, 2016) to safeguard against concerns that our findings are driven by any single country in our sample (Appendix B.7).

Conclusion

International organizations hold power through the information they provide. This is the case because information structures governments' choices in response to global cooperation problems and helps coordinate government action (Abbott and Snidal, 1998; Mitchell, 2006; Voeten, 2021). Much of this logic rests on the assumption that information provided by IOs is exogenous and largely shielded from government influence. In this paper, we add the insight to the rich literature on the downstream effects of IO information that *upstream information production* in IOs is typically itself a political process that is subject to power, interests, and government influence.

We argue that governments have strong incentives to try shape the contents of IO reports, IO-published country rankings, or other influential IO information outputs if they have the chance to do so. Given the wide reach that many IOs have, influence over information production inside IOs—which happens strictly *before* IOs can disseminate any information—is politically attractive. Governments that manage, already at the time of writing, to influence the text of IO reports so that the contents of these reports aligns with national policy priorities can effectively protect national interests from the downstream effects of IO information.

Our empirical analysis shows that governments intervened in the production of the Summary for Policymakers (SPM) text of the latest key IPCC report on climate mitigation policy. Building on unique, non-public data in the form of written government review comments, we demonstrate that national interests robustly predict governments' attempts to shape SPM text. This is true for the number of comments that governments submit whose national interests are tied to oil production, yet the patterns holds for other forms of national interest as well, although in a somewhat more nuanced way. States with national interests derived from climate vulnerability, industrial production, agricultural production, or beef consumption also comment more actively, yet only on those paragraphs that matter for their national interests. Government interference is hence topic-specific, offering strong evidence that governments seek influence in IO information production strategically.

These results connect well with the large body of work that highlights the distributional nature of climate politics (Colgan, Green, and Hale, 2021; Aklin and Mildenberger, 2020; Gaikwad, Genovese, and Tingley, 2022; Gazmararian and Tingley, 2023; Bolet, Green, and Gonzalez-Eguino, 2024; Bayer and Genovese, 2025) to which we add a distinct observation: Domestic distributive politics matters for international cooperation at a *much earlier stage* than what existing scholarship typically assumes. In what we see as this paper's main contribution, we show that states' national interests matter already in upstream information production in IOs rather than only during negotiations over downstream international cooperation outcomes.

Our core findings have several interesting implications. For scholars studying the role of information in international cooperation, we caution that the information which IOs provide might reflect government interests to a much larger extent than what informational theories of international cooperation tend to concede (see Martin and Simmons, 1998, for an overview). Recognizing that the information that IOs produce as outputs is not necessarily neutral, objective, and free from government influence prompts future research in at least three areas.

First, by conceptualizing information production in IOs as a central (and endogenous) part in institutionalist frameworks of international cooperation, we can develop a more refined understanding of the conditions under which governments seek influence in information production as a substitute for or complement to other forms of influence in global governance. Second, as the ability of governments to shape information production in IOs depends on how restrictive or permissive organizational rules are, future research should study the determinants and effects of institutional design for information production across different IOs and how such influence conditions the credibility of IO information. And third, our work signposts research on international cooperation in highly technical issue areas, such as on cyber security, cryptocurrencies, antimicrobial resistance or artificial intelligence, to pay careful attention to information production in IOs. In all these cases, IOs are particularly reliant on governments' specialist resources in terms of data, expertise, and staffing for producing their reports and other IO information products. This creates a largely underappreciated structural dependence of IOs that arises from their need for information inputs. At the same time, it opens the door for governments, many of which are becoming increasingly populist, to allow them influence in IO information production. Our key insight from this paper that governments can shape IO outputs at the point of upstream information production holds important consequences for our understanding of how information matters in and for IOs and for global governance more broadly.

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Government Influence in Information Production in International Organizations

—SUPPLEMENTARY MATERIALS—

Contents

A Data description

A.1 Country covariates

Table A.1 summarizes how we measure the relevant country covariates used in the analysis. Table A.2 summarizes the sources we used to construct these covariates. Finally, in Table A.3, we present basic descriptive statistics of all variables used in the analysis: country covariates, the outcome variables relative to country commenting on POTs, and the topic variables relative to the POTs.

Variable name	Unit	Relevant years
Oil capital per capita	Constant 2018 US$ (log of K)	Average, 2015–2021
Membership in the "SIDS"	Binary	—
Industry, value added	Constant 2015 US$ (log of T)	Average, 2015–2021
Agriculture, forestry, and fishing, value added	Constant 2015 US$ (log of T)	Average, 2015–2021
Bovine meat consumption, value	Constant 2014-2016 US$ (log of B)	Average, 2015–2021
CO_2 emissions	Kg per 2015 US$ of GDP	Average, 2015–2021
GDP	Constant 2015 US$ (T)	Average, 2015–2021
GDP growth	Annual %	Average, 2015–2021
Natural resources	% of GDP	Average, 2015–2021
Nature research leaders	Count, articles in nat, sci. journals	Average, 2015–2021
WGIII AR6 delegation size	Count	2021
Anglophone country	Binary	—

TABLE A.1: Description of country covariates used in the analysis

Variable name	Source	Source URL	Series name
Oil capital per capita	WB "Changing Wealth of Nations"	Downloaded here	`NW.NCA.SAOI.PC`
Membership in the "SIDS"	United Nations	Downloaded here	—
Industry, value added	WB Development Indicators	Arel-Bundock (2022)	`NV.IND.TOTL.KD`
Agriculture, forestry, and fishing, value added	WB Development Indicators	Arel-Bundock (2022)	`NV.AGR.TOTL.KD`
Bovine meat consumption, value	FAO Food Balances statistics	Downloaded here	—
CO_2 emissions	WB Development Indicators	Arel-Bundock (2022)	`EN.ATM.CO2E.KD.GD`
GDP	WB Development Indicators	Arel-Bundock (2022)	`NY.GDP.MKTP.KD`
GDP growth	WB Development Indicators	Arel-Bundock (2022)	`NY.GDP.MKTP.KD.ZG`
Natural resources	WB Development Indicators	Arel-Bundock (2022)	`NY.GDP.TOTL.RT.ZS`
Nature research leaders	*Nature*	Downloaded here	—
WGIII AR6 delegation size	IPCC statistics	Bayer et al. (2024)	—
Anglophone country	CIA World Factbook	Accessed here	—

TABLE A.2: Description of sources for country covariates used in the analysis

A.2 Country comments

In Figure A.1 we present the number of government comments by POT of the draft SPM of WGIII in AR6. We highlight with different colors POTs referring to CCS and AFOLU.

Table A.3: Summary statistics of relevant variables, dyadic dataset

	N	Mean	SD	Min	P25	Median	P75	Max
Comments (count)	1680	4.26	8.07	0.00	0.00	1.00	5.00	70.00
Comments (binary)	1680	0.61	0.49	0.00	0.00	1.00	1.00	1.00
Oil capital per capita (log)	1640	0.74	1.18	0.00	0.00	0.11	0.90	5.17
Membership in the "SIDS" (binary)	1680	0.12	0.32	0.00	0.00	0.00	0.00	1.00
Industry, value added (log)	1680	0.24	0.37	0.00	0.06	0.11	0.29	1.85
Agriculture, forestry, and fishing, value added (log)	1680	0.04	0.12	0.00	0.00	0.01	0.03	0.71
Bovine meat consumption, value (log)	1640	1.08	1.05	0.00	0.31	0.76	1.64	3.92
Topic: CCS (binary)	1680	0.07	0.26	0.00	0.00	0.00	0.00	1.00
Topic: AFOLU (binary)	1680	0.10	0.30	0.00	0.00	0.00	0.00	1.00
Topic: CCS (binary, keyATM)	1680	0.05	0.22	0.00	0.00	0.00	0.00	1.00
Topic: AFOLU (binary, keyATM)	1680	0.03	0.16	0.00	0.00	0.00	0.00	1.00
Topic: CCS (proportion, keyATM)	1680	0.05	0.08	0.00	0.00	0.02	0.06	0.41
Topic: AFOLU (proportion, keyATM)	1680	0.04	0.07	0.00	0.00	0.03	0.05	0.32
CO_2 emissions (kg)	1680	0.41	0.34	0.05	0.18	0.26	0.53	1.42
GDP (trillions)	1680	1.57	3.52	0.00	0.19	0.40	1.45	19.28
GDP growth (%)	1680	2.05	2.10	-2.65	1.02	1.66	2.78	9.87
Natural resources (GDP %)	1680	2.98	5.40	0.00	0.07	0.77	3.40	23.74
Nature research leaders (count)	1680	2.44	4.94	0.00	0.22	0.69	2.34	28.01
WGIII AR6 delegation size (count)	1640	9.15	7.79	1.00	3.00	7.00	13.00	30.00
Anglophone country (binary)	1680	0.29	0.45	0.00	0.00	0.00	1.00	1.00

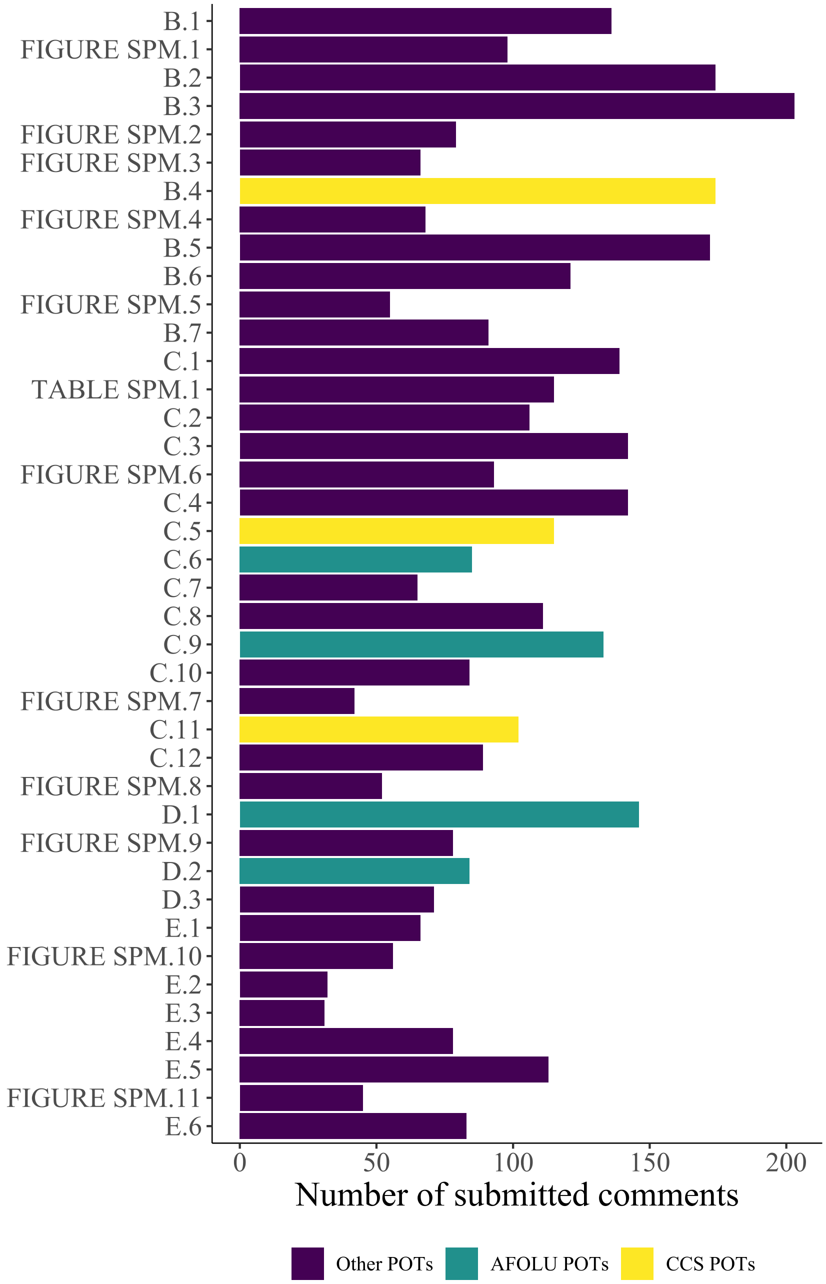

FIGURE A.1: Number of government comments by POT of the WGIII SPM draft text.

B Robustness Tests

B.1 Full disclosure of estimates in Table 2

In Tables B.1, we disclose all estimates relative to models in Table 2 (including omitted covariates).

Table B.1: Logistic regression results for interaction models of national interest and topic-specific parts of text (full disclosure)

	Dependent variable: Comments (binary)											
	SIDS[1]			Industry[2]			Agriculture[3]			Meat[4]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
National interest	-0.011	0.555	0.581	2.392	5.244*	5.513*	2.525	2.607	2.737	0.280	-0.116	-0.123
	(0.571)	(1.160)	(1.219)	(1.491)	(2.098)	(2.164)	(2.151)	(6.409)	(6.760)	(0.236)	(0.297)	(0.313)
National interest × Topic: CCS	0.744***	0.883***	0.934***	4.426**	3.640***	3.933***						
	(0.111)	(0.259)	(0.264)	(1.631)	(0.813)	(0.948)						
National interest × Topic: AFOLU							15.916*	10.770***	11.321**	0.305***	0.358**	0.379**
							(7.869)	(2.732)	(3.524)	(0.019)	(0.111)	(0.142)
Topic: CCS	0.236	0.276		-0.181	-0.083							
	(0.242)	(0.298)		(0.250)	(0.308)							
Topic: AFOLU							-0.433*	-0.378		-0.409*	-0.456*	
							(0.211)	(0.250)		(0.185)	(0.229)	
CO_2 emissions (kg)		-0.835	-0.880		-1.156	-1.216		-1.095	-1.155		-0.919	-0.968
		(0.725)	(0.766)		(0.754)	(0.796)		(0.671)	(0.708)		(0.750)	(0.793)
GDP (trillinos)		-0.455	-0.474		-1.088**	-1.141*		-0.624	-0.651		-0.347	-0.361
		(0.366)	(0.384)		(0.420)	(0.443)		(0.527)	(0.555)		(0.355)	(0.370)
GDP growth (%)		-0.054	-0.057		-0.120	-0.127		-0.119	-0.125		-0.103	-0.109
		(0.115)	(0.122)		(0.099)	(0.104)		(0.119)	(0.126)		(0.109)	(0.116)
Natural resources (GDP %)		0.086	0.091		0.076	0.080		0.087+	0.092+		0.080	0.084
		(0.053)	(0.056)		(0.049)	(0.051)		(0.047)	(0.049)		(0.050)	(0.052)
Nature research leaders (count)		0.610*	0.636*		0.576*	0.601*		0.644*	0.671*		0.538*	0.561*
		(0.270)	(0.285)		(0.242)	(0.256)		(0.258)	(0.270)		(0.240)	(0.252)
WGIII AR6 delegation size (count)		0.028	0.029		-0.017	-0.018		0.021	0.022		0.022	0.023
		(0.033)	(0.035)		(0.034)	(0.036)		(0.032)	(0.034)		(0.034)	(0.035)
Anglophone country (bin)		0.657+	0.688+		1.012+	1.064+		0.793	0.832		0.840	0.882
		(0.352)	(0.374)		(0.532)	(0.561)		(0.498)	(0.525)		(0.540)	(0.570)
POT-FE			✓			✓			✓			✓
Clustered SE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Num.Obs.	1680	1640	1640	1680	1640	1640	1680	1640	1640	1640	1640	1640
R2	0.002	0.127	0.161	0.068	0.139	0.173	0.017	0.127	0.162	0.018	0.124	0.158
R2 Adj.	-0.001	0.118	0.117	0.065	0.130	0.130	0.014	0.118	0.118	0.016	0.115	0.115

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001
[1]National interest measure: Membership in the "Small Islands Developing States" (binary). Source: UN
[2]National interest measure: Industry, value added (trillions of 2015 US $, logs). Source: WDI data
[3]National interest measure: Agriculture, forestry, and fishing, value added (trillions of 2015 US $, logs). Source: WDI data
[4]National interest measure: Bovine meat consumption, value (billions of 2014–2016 international $, logs). Source: FAO data
Note: Dyadic dataset of 42 countries × 40 parts of text (POTs). All models are logistic regressions a binary indidcator of whether a government submitted at least one comment (= 1) or not (= 0) for each POT as outcome variable. Variables are averaged over 2015-2021 period. Standard errors are clustered at the country-level and POT-level. 'CCS' stands for 'carbon capture and storage' technology; 'AFOLU' stands for 'agriculture, forestry, and other land use'.

B.2 Non-transformed Explanatory Variables

In Tables B.2 and B.3, we replicate our main analysis without log-transforming any of our right-hand side variables. Results are similar to those presented in the main text.

Table B.2: The effect of oil capital on country attempts to interfere with IPCC information production

	Dependent variable: Comments (count)			
	(1)	(2)	(3)	(4)
Oil capital per capita	0.009***	0.013***	0.019+	0.019*
	(0.002)	(0.002)	(0.010)	(0.009)
CO_2 emissions (kg)		-1.493*	-1.436	-0.706
		(0.657)	(1.062)	(1.271)
GDP (trillions)			0.122***	-0.301**
			(0.011)	(0.115)
GDP growth (%)			-0.089	-0.035
			(0.075)	(0.067)
Natural resources (GDP %)			-0.035	-0.034
			(0.089)	(0.088)
Nature research leaders (count)				0.278**
				(0.088)
WGIII AR6 delegation size (count)				0.019
				(0.014)
Anglophone country (binary)				0.161
				(0.249)
POT-FE	✓	✓	✓	✓
Clustered SE	✓	✓	✓	✓
Num.Obs.	1640	1640	1640	1640
R2	0.141	0.193	0.391	0.440
R2 Adj.	0.136	0.189	0.387	0.435

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Dyadic dataset of 42 countries $\times$ 40 parts of text (POTs). All models are Poisson regressions with the number of government-submitted comments for each POT as outcome variable. Variables are averaged over 2015-2021 period. POT-level fixed effects are included in all models. Standard errors are clustered at the country-level and POT-level.

Table B.3: The effect of national and topic on country attempts to interfere with IPCC information production

	Dependent variable: Comments (binary)											
	SIDS[1]			Industry[2]			Agriculture[3]			Meat[4]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
National interest	-0.011	0.555	0.581	0.710	-3.154	-3.288	1.567	0.630	0.656	0.018	-0.028	-0.029
	(0.571)	(1.160)	(1.219)	(0.786)	(2.132)	(2.234)	(1.381)	(4.945)	(5.201)	(0.024)	(0.022)	(0.023)
National interest × Topic: CCS	0.744***	0.883***	0.934***	5.116***	2.917***	3.157***						
	(0.111)	(0.259)	(0.264)	(1.405)	(0.546)	(0.651)						
National interest × Topic: AFOLU							15.914*	10.095***	10.601***	0.027	0.036***	0.038*
							(7.886)	(2.220)	(2.952)	(0.018)	(0.009)	(0.016)
Topic: CCS	0.236	0.276		-0.389	-0.045							
	(0.242)	(0.298)		(0.268)	(0.283)							
Topic: AFOLU							-0.447*	-0.378		-0.221	-0.257	
							(0.211)	(0.250)		(0.164)	(0.211)	
Controls		✓	✓		✓	✓		✓	✓		✓	✓
POT-FE			✓			✓			✓			✓
Clustered SE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Num.Obs.	1680	1640	1640	1680	1640	1640	1680	1640	1640	1640	1640	1640
R2	0.002	0.127	0.161	0.043	0.141	0.175	0.015	0.126	0.160	0.008	0.126	0.160
R2 Adj.	-0.001	0.118	0.117	0.040	0.131	0.131	0.012	0.117	0.117	0.005	0.117	0.117

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001
[1]National interest measure: Membership in the "Small Islands Developing States" (binary). Source: UN
[2]National interest measure: Industry, value added (trillions of 2015 US $). Source: WDI data
[3]National interest measure: Agriculture, forestry, and fishing, value added (trillions of 2015 US $). Source: WDI data
[4]National interest measure: Bovine meat consumption, value (billions of 2014–2016 international $). Source: FAO data
Note: Dyadic dataset of 42 countries × 40 parts of text (POTs). All models are logistic regressions a binary indidcator of whether a government submitted at least one comment (= 1) or not (= 0) for each POT as outcome variable. Variables are averaged over 2015-2021 period. Standard errors are clustered at the country-level and POT-level. 'CCS' stands for 'carbon capture and storage' technology; 'AFOLU' stands for 'agriculture, forestry, and other land use'.

B.3 OLS Models

In Tables B.4 and B.5 we show that our findings are robust to estimating our models with ordinary least squares (OLS) rather than as count models or logistic regressions.

Table B.4: The effect of oil capital on country attempts to interfere with IPCC information production

	Dependent variable: Comments (count)			
	(1)	(2)	(3)	(4)
Oil capital per capita (log)	1.581*	2.364***	1.967*	1.841
	(0.730)	(0.648)	(0.885)	(1.193)
CO_2 emissions (kg)		-6.232*	-7.310*	-4.637+
		(2.555)	(3.431)	(2.571)
GDP (trillions)			1.135***	-1.346*
			(0.270)	(0.584)
GDP growth (%)			-0.365	-0.210
			(0.370)	(0.243)
Natural resources (GDP %)			0.124	0.157
			(0.230)	(0.255)
Nature research leaders (count)				1.766***
				(0.401)
WGIII AR6 delegation size (count)				0.019
				(0.075)
Anglophone country (binary)				1.737
				(1.147)
POT-FE	✓	✓	✓	✓
Clustered SE	✓	✓	✓	✓
Num.Obs.	1640	1640	1640	1640
R2	0.111	0.164	0.396	0.461
R2 Adj.	0.089	0.143	0.379	0.446

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Dyadic dataset of 42 countries × 40 parts of text (POTs). All models are linear regressions with the number of government-submitted comments for each POT as outcome variable. Variables are averaged over 2015-2021 period. POT-level fixed effects are included in all models. Standard errors are clustered at the country-level and POT-level.

Table B.5: The effect of national interest and topic on country attempts to interfere with IPCC information production

	Dependent variable: Comments (binary)											
	SIDS[1]			Industry[2]			Agriculture[3]			Meat[4]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
National interest	-0.003	0.111	0.111	0.321*	0.926***	0.926***	0.456	1.305*	1.305*	0.063	-0.008	-0.008
	(0.135)	(0.224)	(0.225)	(0.119)	(0.220)	(0.221)	(0.280)	(0.528)	(0.530)	(0.049)	(0.068)	(0.068)
National interest × Topic: CCS	0.145***	0.157***	0.157***	0.060*	0.064	0.064						
	(0.014)	(0.005)	(0.004)	(0.028)	(0.063)	(0.061)						
National interest × Topic: AFOLU							0.451***	0.453***	0.453***	0.060***	0.060**	0.060***
							(0.028)	(0.030)	(0.034)	(0.011)	(0.018)	(0.009)
Topic: CCS	0.055	0.055		0.058	0.054							
	(0.056)	(0.056)		(0.054)	(0.069)							
Topic: AFOLU							-0.047	-0.048		-0.092+	-0.092+	
							(0.059)	(0.056)		(0.052)	(0.055)	
Controls		✓	✓		✓	✓		✓	✓		✓	✓
POT-FE			✓			✓			✓			✓
Clustered SE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Num.Obs.	1680	1640	1640	1680	1640	1640	1680	1640	1640	1640	1640	1640
R2	0.002	0.108	0.145	0.064	0.150	0.187	0.016	0.132	0.171	0.023	0.104	0.142
R2 Adj.	0.000	0.103	0.119	0.062	0.145	0.163	0.014	0.127	0.146	0.022	0.098	0.116

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

[1]National interest measure: Membership in the "Small Islands Developing States" (binary). Source: UN

[2]National interest measure: Industry, value added (trillions of 2015 US $, logs). Source: WDI data

[3]National interest measure: Agriculture, forestry, and fishing, value added (trillions of 2015 US $, logs). Source: WDI data

[4]National interest measure: Bovine meat consumption, value (billions of 2014–2016 international $, logs). Source: FAO data

Note: Dyadic dataset of 42 countries × 40 parts of text (POTs). All models are linear regressions a binary indidcator of whether a government submitted at least one comment (= 1) or not (= 0) for each POT as outcome variable. Variables are averaged over 2015-2021 period. Standard errors are clustered at the country-level and POT-level. 'CCS' stands for 'carbon capture and storage' technology; 'AFOLU' stands for 'agriculture, forestry, and other land use'.

B.4 Alternative Outcome Measures

In Tables B.6 and B.7, we replicate our main analysis when we use binary outcomes instead of counts for our first set of models and counts instead of binary outcomes for our second set of models. We find that oil capital matters primarily for the intensity with which governments engage, that is, for the number of submitted comments, but much less so whether they submit comments at all or not. For our interaction effects, we find less of a difference to the models presented in the main text, even though the evidence for a positive interaction effect of national interest and the CCS topic weakens.

Table B.6: The effect of oil capital on country attempts to interfere with IPCC information production

	Dependent variable: Comments (binary)			
	(1)	(2)	(3)	(4)
Oil capital per capita (log)	0.174	0.302	0.358	0.283
	(0.181)	(0.202)	(0.309)	(0.315)
CO_2 emissions (kg)		-0.927	-0.971	-0.739
		(0.669)	(0.879)	(0.764)
GDP (trillions)			0.346	-0.414
			(0.310)	(0.356)
GDP growth (%)			-0.059	-0.088
			(0.131)	(0.112)
Natural resources (GDP %)			-0.015	0.025
			(0.082)	(0.080)
Nature research leaders (count)				0.585*
				(0.257)
WGIII AR6 delegation size (count)				0.013
				(0.034)
Anglophone country (binary)				0.858+
				(0.512)
POT-FE	✓	✓	✓	✓
Clustered SE	✓	✓	✓	✓
Num.Obs.	1640	1640	1640	1640
R2	0.036	0.049	0.113	0.160
R2 Adj.	-0.000	0.012	0.073	0.117

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Dyadic dataset of 42 countries $\times$ 40 parts of text (POTs). All models are logistic regressions with the number of government-submitted comments for each POT as outcome variable. Variables are averaged over 2015-2021 period. POT-level fixed effects are included in all models. Standard errors are clustered at the country-level and POT-level.

Table B.7: The effect of national interest and topic on country attempts to interfere with IPCC information production

	Dependent variable: Comments (count)											
	SIDS[1]			Industry[2]			Agriculture[3]			Meat[4]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
National interest	-0.600+	0.215	0.215	1.055*	1.548***	1.548***	1.131	4.079**	4.079**	0.373+	-0.005	-0.005
	(0.350)	(0.541)	(0.541)	(0.413)	(0.442)	(0.452)	(1.114)	(1.412)	(1.427)	(0.211)	(0.217)	(0.217)
National interest × Topic: CCS	-0.033	-0.098+	-0.098*	0.022	0.036	0.036						
	(0.117)	(0.055)	(0.044)	(0.022)	(0.034)	(0.022)						
National interest × Topic: AFOLU							0.361***	0.571***	0.571***	0.037**	0.031	0.031
							(0.045)	(0.133)	(0.128)	(0.013)	(0.036)	(0.020)
Topic: CCS	0.341***	0.341***		0.328***	0.317***							
	(0.080)	(0.033)		(0.023)	(0.043)							
Topic: AFOLU							0.308***	0.294**		0.276***	0.286***	
							(0.016)	(0.090)		(0.035)	(0.061)	
Controls		✓	✓		✓	✓		✓	✓		✓	✓
POT-FE			✓			✓			✓			✓
Clustered SE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Num.Obs.	1680	1640	1640	1680	1640	1640	1680	1640	1640	1640	1640	1640
R2	0.014	0.334	0.414	0.130	0.347	0.427	0.016	0.357	0.436	0.082	0.334	0.413
R2 Adj.	0.014	0.333	0.409	0.129	0.346	0.421	0.016	0.356	0.431	0.082	0.333	0.408

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[1]National interest measure: Membership in the “Small Islands Developing States” (binary). Source: UN

[2]National interest measure: Industry, value added (trillions of 2015 US $, logs). Source: WDI data

[3]National interest measure: Agriculture, forestry, and fishing, value added (trillions of 2015 US $, logs). Source: WDI data

[4]National interest measure: Bovine meat consumption, value (billions of 2014–2016 international $, logs). Source: FAO data

Note: Dyadic dataset of 42 countries × 40 parts of text (POTs). All models are Poisson regressions of the number of government-submitted comments for each POT as outcome variable. Variables are averaged over 2015-2021 period. Standard errors are clustered at the country-level and POT-level. ‘CCS’ stands for ‘carbon capture and storage’ technology; ‘AFOLU’ stands for ‘agriculture, forestry, and other land use’.

B.5 Topic-specific effects: placebos

In Table B.8 we interact our oil capital per capita variable with topics indicating CCS or AFOLU POTs. We intend this as a placebo test confirming our interpretation (grounded in existing research) that oil interests structure opposition to climate policy across the board. Consistently, we find that the effect of oil capital per capita is not conditional of the specific climate policy option discussed in the text.

Table B.8: Poisson regression results for interaction models of oil capital and topic-specific parts of text

	Dependent variable: Comments (count)			
	(1)	(2)	(3)	(4)
Oil capital per capita (log)	0.273***	0.387*	0.260**	0.373*
	(0.080)	(0.168)	(0.081)	(0.170)
Oil capital per capita × Topic: CCS	-0.069	-0.076		
	(0.051)	(0.074)		
Oil capital per capita × Topic: AFOLU			0.043*	0.047
			(0.021)	(0.033)
Topic: CCS	0.418***			
	(0.010)			
Topic: AFOLU			0.280***	
			(0.042)	
Controls		✓		✓
POT-FE		✓		✓
Clustered SE	✓	✓	✓	✓
Num.Obs.	1640	1640	1640	1640
R2	0.061	0.433	0.062	0.433
R2 Adj.	0.061	0.428	0.061	0.427

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Dyadic dataset of 42 countries × 40 parts of text (POTs). All models are Poisson regressions with the number of government-submitted comments for each POT as outcome variable. Variables are averaged over 2015-2021 period. POT-level fixed effects are included in all models. Standard errors are clustered at the country-level and POT-level.

In Table B.9 we replicate results from Table 2 but refrain from interacting exposure variables with topic indicators. We intend this as a placebo test that the effect of these national interests on attempts at interfering with information production is conditional on the discussed topic. We indeed find that climate policy exposure indicators do not affect the probability to submit a comment unconditionally from the topic being discussed.

Table B.9: Logistic regression results for unconditional models of national interest

	Dependent variable: Comments (binary)							
	SIDS[1]		Industry[2]		Agriculture[3]		Meat[4]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
National interest	0.035	0.636	2.540+	5.687**	2.912	3.257	0.308	-0.085
	(0.566)	(1.218)	(1.532)	(2.198)	(2.368)	(6.587)	(0.236)	(0.308)
Controls		✓		✓		✓		✓
POT-FE		✓		✓		✓		✓
Clustered SE	✓	✓	✓	✓	✓	✓	✓	✓
Num.Obs.	1680	1640	1680	1640	1680	1640	1640	1640
R2	0.000	0.160	0.064	0.171	0.013	0.159	0.017	0.157
R2 Adj.	-0.001	0.117	0.063	0.128	0.012	0.116	0.016	0.114

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[1]National interest measure: Membership in the "Small Islands Developing States" (binary). Source: UN

[2]National interest measure: Industry, value added (trillions of 2015 US $, logs). Source: WDI data

[3]National interest measure: Agriculture, forestry, and fishing, value added (trillions of 2015 US $, logs). Source: WDI data

[4]National interest measure: Bovine meat consumption, value (billions of 2014–2016 international $, logs). Source: FAO data

Note: Dyadic dataset of 42 countries × 40 parts of text (POTs). All models are logistic regressions a binary indidcator of whether a government submitted at least one comment (= 1) or not (= 0) for each POT as outcome variable. Variables are averaged over 2015-2021 period. Standard errors are clustered at the country-level and POT-level. 'CCS' stands for 'carbon capture and storage' technology; 'AFOLU' stands for 'agriculture, forestry, and other land use'.

B.6 Results for keyATM-derived Topic Classification

For our main analysis, we identify POTs that relate to CCS technology and emissions from agriculture, forestry and other land use (AFOLU) through qualitative coding of POT contents. Here, we use a semi-supervised topic model, keyATM model (Eshima, Imai, and Sasaki, 2024), to help us identify relevant POTs from information about the expected main topic and topic proportions. Results are very similar.

We start by pre-processing the SPM parts of text in the usual way (e.g., stemming, lowercasing, defining compound expressions, removing stop words) before fitting a keyATM model with the following ten labeled topics in addition to two unlabeled ones: Gases and emissions; Temperatures/scenarios; Policy/political responses; Transports, building, industry; Technology/investment; Fossil-fuels; Renewable energy; Carbon Removal (our CCS target topic); Land use (our AFOLU target topic); and IPCC terminology. We present the keywords supplied to the model together with their frequency in the corpus in Figure B.1.

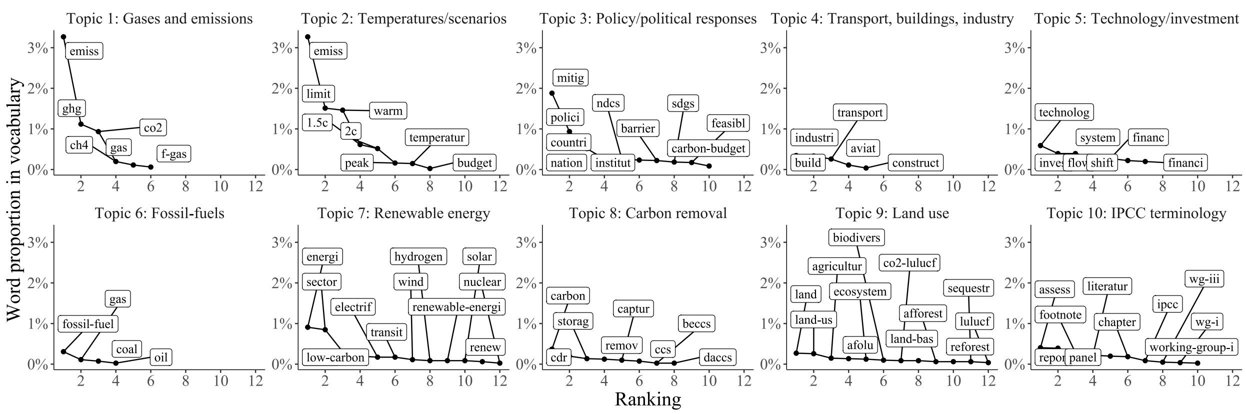

FIGURE B.1: Frequency of keywords for the ten labeled topics supplied to keyATM.

Table B.10 presents the top-15 words for each of the ten labeled and two unlabeled topics as estimated from the keyATM model. The model performs well overall as it successfully allocates the majority of topics to our pre-defined labels. Figure B.2 plots the predicted topic proportions and the top-10 predicted words for each of the topics.

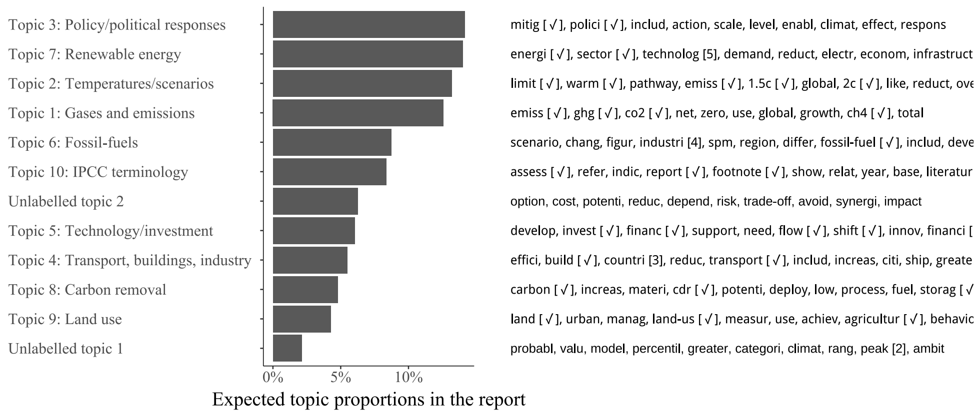

FIGURE B.2: Frequency of predicted topics from keyATM with top-10 words for each topic.

Predicted topic proportions for each POT are shown in Figure B.3. The assignment of topics to POTs from the topic model is reassuringly consistent with our qualitative analysis and our reading of the SPM text. We use a binary measure for whether a POT was classified as primarily related to CCS or AFOLU as well as continuous topic proportions per POT to construct a keyATM-derived variable that can be used in our regression models as the topic-specific interaction term.

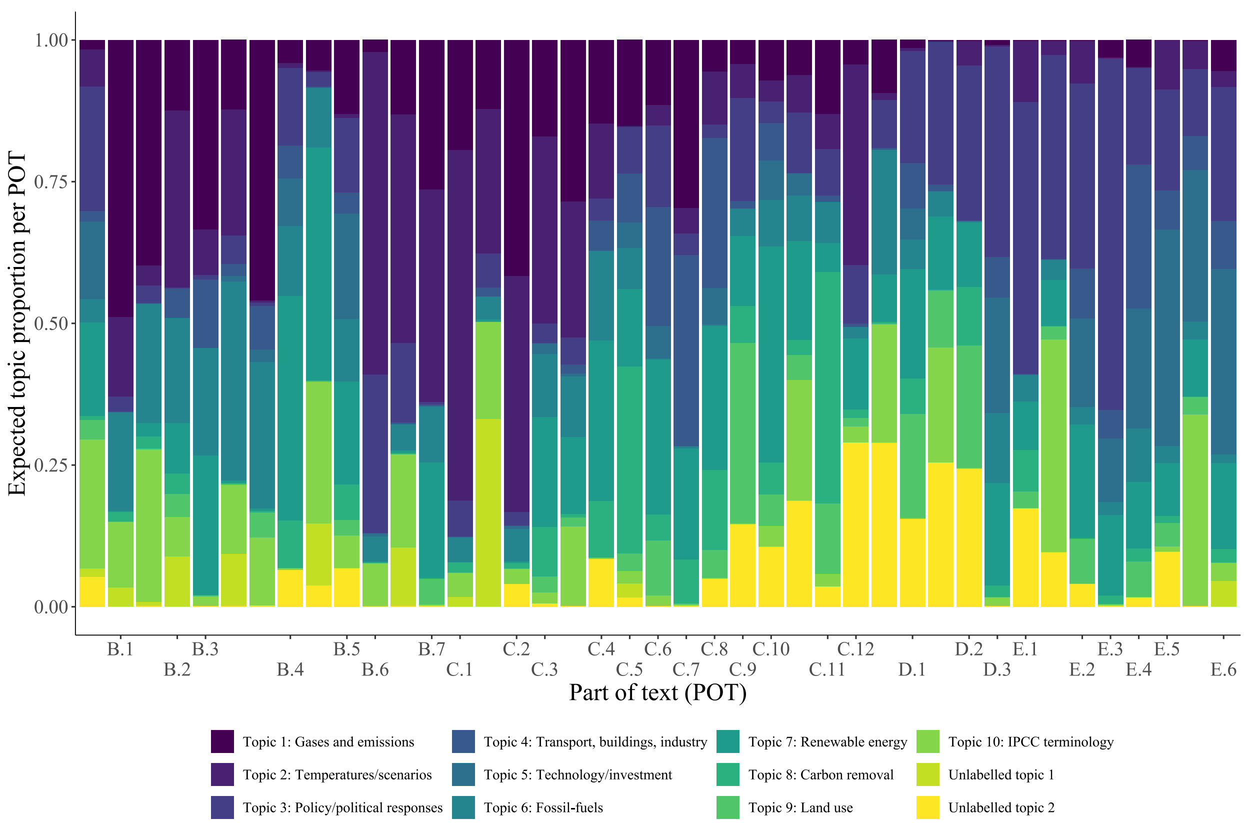

FIGURE B.3: Proportion of predicted topics per POT as estimated from keyATM model.

Table B.10: Top 15 words of the 12 labelled topics and 2 unlabelled topics. Topic estimation via keyATM

Topic 1: Gases and emissions	Topic 2: Temperatures/scenarios	Topic 3: Policy/political responses	Topic 4: Transport, buildings, industry
emiss [✓]	limit [✓]	mitig [✓]	effici
ghg [✓]	warm [✓]	polici [✓]	build [✓]
co2 [✓]	pathway	includ	countri [Topic 3]
net	emiss [✓]	action	reduc
zero	1.5c [✓]	scale	transport [✓]
use	global	level	includ
global	2c [✓]	enabl	increas
growth	like	climat	citi
ch4 [✓]	reduct	effect	ship
total	overshoot	respons	greater
sinc	current	across	region
remain	gtco2-eq	ndcs [✓]	area
less	spm	institut [✓]	aviat [✓]
time	level	implement	popul
gtco2	rang	barrier [✓]	design
Topic 5: Technology/investment	Topic 6: Fossil-fuels	Topic 7: Renewable energy	Topic 8: Carbon removal
develop	scenario	energi [✓]	carbon [✓]
invest [✓]	chang	sector [✓]	increas
financ [✓]	figur	technolog [Topic 5]	materi
support	industri [Topic 4]	demand	cdr [✓]
need	spm	reduct	potenti
flow [✓]	region	electr	deploy
shift [✓]	differ	econom	low
innov	fossil-fuel [✓]	infrastructur	process
financi [✓]	includ	capac [✓]	fuel
intern	develop	climate-chang	storag [✓]
multipl	well	high	resourc
instrument	system [Topic 5]	global	remov [✓]
govern	term	sustain	heat
choic	consist	context	deep
public	rate	improv	method
Topic 9: Land use	Topic 10: IPCC terminology	Unlabelled topic 1	Unlabelled topic 2
land [✓]	assess [✓]	probabl	option
urban	refer	valu	cost
manag	indic	model	potenti
land-us [✓]	report [✓]	percentil	reduc
measur	footnote [✓]	greater	depend
use	show	categori	risk
achiev	relat	climat	trade-off
agricultur [✓]	year	rang	avoid
behaviour	base	peak [Topic 2]	synergi
co-benefit	literatur [✓]	ambit	impact
afolu [✓]	panel [✓]	share	benefit
exist	averag	throughout	adapt
ecosystem [✓]	data	emul	figur
soil	chapter [✓]	calcul	demand-sid
biodivers [✓]	given	bracket	specif

When we substitute our manually coded topic dummy for CCS and AFOLU with a keyATM-derived equivalent that scores '1' when CCS or AFOLU, respectively, are predicted to be the top topic and zero otherwise, we find very similar results (TableB.11). Except for the measure that operationalizes national interest as the value added from agricultural production (models (7)-(9)), we continue to find statistically significant interaction terms even when using continuous topic proportions for CCS and AFOLU as predicted from the keyATM model (Table B.12). This provides strong reassurance for the robustness of our analysis.

Table B.11: The effect of climate policy exposure and topic on country attempts to interfere with IPCC information production

	Dependent variable: Comments (binary)											
	SIDS[1]			Industry[2]			Agriculture[3]			Meat[4]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Climate policy exposure	-0.009	0.576	0.605	2.426	5.268*	5.552*	2.839	3.035	3.185	0.299	-0.093	-0.099
	(0.592)	(1.161)	(1.220)	(1.502)	(2.106)	(2.175)	(2.319)	(6.307)	(6.651)	(0.238)	(0.297)	(0.311)
Climate policy exposure × Topic: CCS (keyATM)	1.012***	0.649+	0.648*	4.207*	3.975***	3.961***						
	(0.276)	(0.332)	(0.319)	(1.652)	(0.861)	(0.984)						
Climate policy exposure × Topic: AFOLU (keyATM)							35.307***	25.887***	25.475***	0.605***	0.668***	0.668***
							(2.302)	(0.497)	(0.590)	(0.053)	(0.155)	(0.141)
Topic: CCS (keyATM)	-0.053	-0.063		-0.472**	-0.518*							
	(0.095)	(0.201)		(0.164)	(0.215)							
Topic: AFOLU (keyATM)							-0.039	0.091		-0.037	-0.033	
							(0.048)	(0.175)		(0.166)	(0.268)	
Controls		✓	✓		✓	✓		✓	✓		✓	✓
POT-FE			✓			✓			✓			✓
Clustered SE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Num.Obs.	1680	1640	1640	1680	1640	1640	1680	1640	1640	1640	1640	1640
R2	0.001	0.126	0.160	0.066	0.138	0.173	0.015	0.126	0.160	0.018	0.124	0.158
R2 Adj.	-0.002	0.117	0.117	0.063	0.128	0.129	0.013	0.117	0.116	0.016	0.115	0.114

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

[1]Climate policy exposure: Membership in the "Small Islands Developing States" (binary). Source: UN

[2]Climate policy exposure: Industry, value added (trillions of 2015 US $, logs). Source: WDI data

[3]Climate policy exposure: Agriculture, forestry, and fishing, value added (trillions of 2015 US $, logs). Source: WDI data

[4]Climate policy exposure: Bovine meat consumption, value (billions of 2014–2016 international $, logs). Source: FAO data

Note: Dyadic dataset of 42 countries × 40 parts of text (POTs). All models are logistic regressions a binary indidcator of whether a government submitted at least one comment (= 1) or not (= 0) for each POT as outcome variable. Variables are averaged over 2015-2021 period. Standard errors are clustered at the country-level and POT-level. 'CCS' stands for 'carbon capture and storage' technology; 'AFOLU' stands for 'agriculture, forestry, and other land use'.

Table B.12: The effect of climate policy exposure and topic on country attempts to interfere with IPCC information production

	Dependent variable: Comments (binary)											
	SIDS[1]			Industry[2]			Agriculture[3]			Meat[4]		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Climate policy exposure	-0.105	0.527	0.557	1.880	4.748*	5.032*	2.377	2.521	2.594	0.243	-0.161	-0.174
	(0.586)	(1.159)	(1.218)	(1.503)	(2.059)	(2.132)	(1.953)	(6.300)	(6.639)	(0.242)	(0.306)	(0.321)
Climate policy exposure × Topic: CCS (prop., keyATM)	3.068***	1.686***	1.658***	19.827*	16.863***	16.769***						
	(0.191)	(0.129)	(0.099)	(9.297)	(4.326)	(4.558)						
Climate policy exposure × Topic: AFOLU (prop., keyATM)							15.734	14.927	17.390	1.600***	1.902***	2.094***
							(16.111)	(13.007)	(14.889)	(0.235)	(0.399)	(0.518)
Topic: CCS (prop., keyATM)	0.142	0.167		-1.869+	-1.793**							
	(0.525)	(0.727)		(1.126)	(0.640)							
Topic: AFOLU (prop., keyATM)							-0.638	-0.674		-1.745+	-1.963	
							(0.986)	(1.126)		(1.043)	(1.218)	
Controls		✓	✓		✓	✓		✓	✓		✓	✓
POT-FE			✓			✓			✓			✓
Clustered SE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Num.Obs.	1680	1640	1640	1680	1640	1640	1680	1640	1640	1640	1640	1640
R2	0.001	0.126	0.160	0.070	0.141	0.176	0.014	0.125	0.159	0.018	0.124	0.159
R2 Adj.	-0.001	0.117	0.117	0.067	0.132	0.132	0.011	0.116	0.116	0.016	0.115	0.115

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

[1]Climate policy exposure: Membership in the "Small Islands Developing States" (binary). Source: UN

[2]Climate policy exposure: Industry, value added (trillions of 2015 US $, logs). Source: WDI data

[3]Climate policy exposure: Agriculture, forestry, and fishing, value added (trillions of 2015 US $, logs). Source: WDI data

[4]Climate policy exposure: Bovine meat consumption, value (billions of 2014–2016 international $, logs). Source: FAO data

Note: Dyadic dataset of 42 countries × 40 parts of text (POTs). All models are logistic regressions a binary indidcator of whether a government submitted at least one comment (= 1) or not (= 0) for each POT as outcome variable. Variables are averaged over 2015-2021 period. Standard errors are clustered at the country-level and POT-level. 'CCS' stands for 'carbon capture and storage' technology; 'AFOLU' stands for 'agriculture, forestry, and other land use'.

B.7 Regression Implied Weights

We compute implied regression weights for our main measures of national interest to offer evidence that our findings are not the artifact of just a few countries in our sample. We follow the procedure devised by Aronow and Samii (2016) and compute weights from linear regression models given their finding that implied weights in non-linear models are largely similar to those derived from OLS regressions (Aronow and Samii, 2016, 257).

Since regression weights are independent of the outcome and only a function of how much of the 'treatment' variable's variance is unexplained by the other covariates, we first regress each of our national interest measures on all other covariates and fixed effects. We then calculate the squared residuals for each observation together with both the sum of squared residuals for each country and the total sum of squared residuals. Regression-implied weights can then be defined as the ratio of he country sum relative to the total sum of squared residuals. We plot these weights against the distribution of our respective national interest measures as a visual diagnostic to assess any skew.

Figure B.4 shows results for the per capita oil capital variable, which highlight a rather even distribution: large weights are given to some countries with high oil capital values, such as Norway and Canada, but countries with lower oil capital values like Denmark, Estonia, Tanzania, and Chile are also assigned fairly high weights. On the other hand, Saudi Arabia, Iran, and Algeria hold considerable oil capital, but receive small weights.

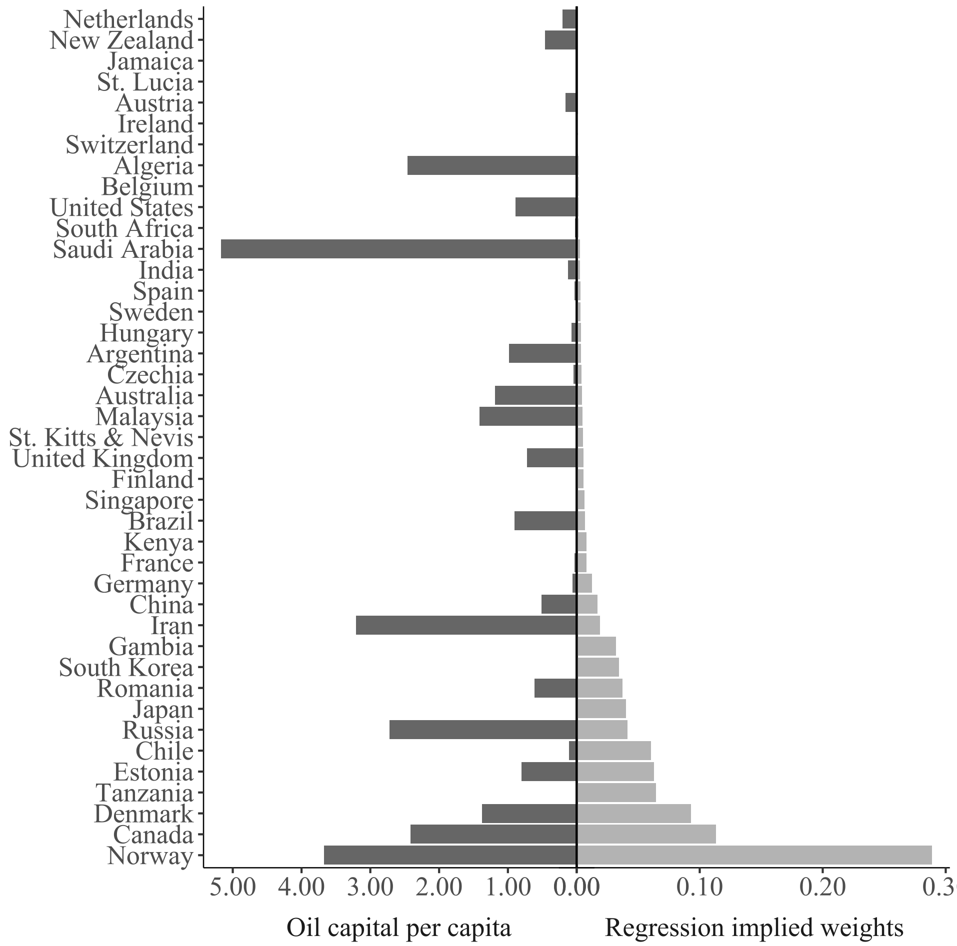

FIGURE B.4: Regression implied weights: oil capital per capita.

We replicate the above procedure for all our different operationalizations of national interest. Figure B.5 shows results for the industry value added variable, for which large weights are assigned to countries with substantial industrial manufacturing capacity like the United States, Japan, China, and Germany. The fact that we find much weight being put on other countries for this measure is important because it offers reassurance that this the industrial composition variable captures a different dimension of national interest, which is exactly what we intended in our empirical strategy.

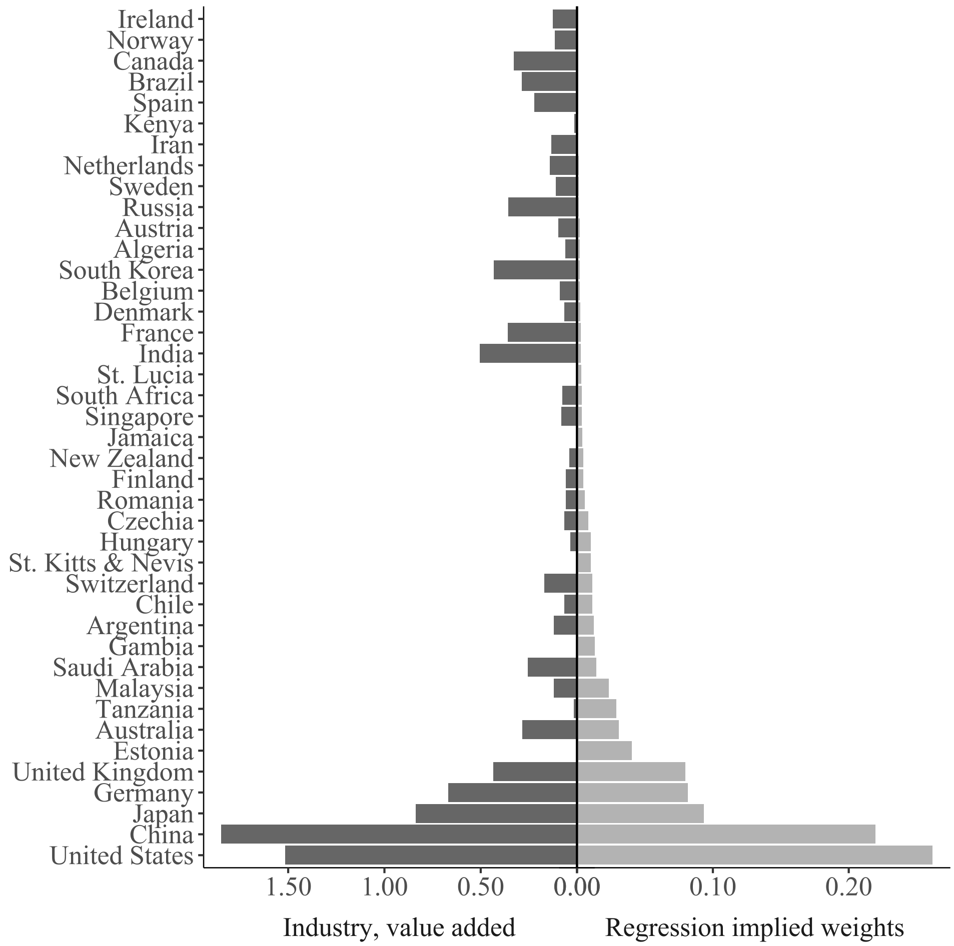

FIGURE B.5: Regression implied weights: industry value added.

We obtain a similar finding for our SIDS dummy which proxies for climate vulnerability. Highest weights are very understandably assigned to countries, such as Singapore, St. Lucia, St. Kitts & Nevis, Jamaica and Palau, all of which are indeed classified as small island developing states by the United Nations, but also to South Africa, Brazil, Argentina, Japan or Ireland, outside of the SIDS grouping. These countries possibly contribute to the estimate in a meaningful way because of their long coastlines or as they are islands themselves, which makes them vulnerable to rising sea levels somewhat similar to SIDS countries, although at a much less existential level.

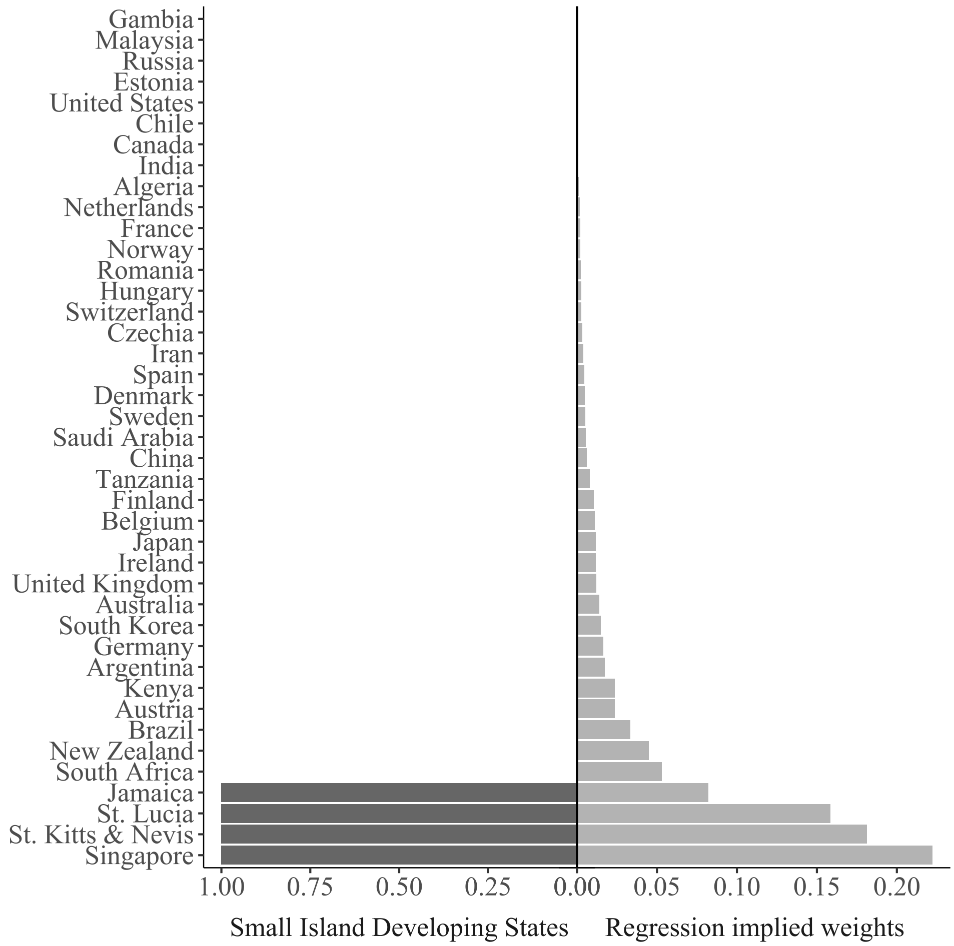

FIGURE B.6: Regression implied weights: SIDS membership.

In the case of our measure for value added from agricultural production, different countries come up on top in terms of implied regression weights again. Figure B.7 shows that China, the United States, India, the United Kingdom, and Japan make the largest contribution to the estimate, which is interesting because of low values for the UK and Japan for their value added from agriculture.

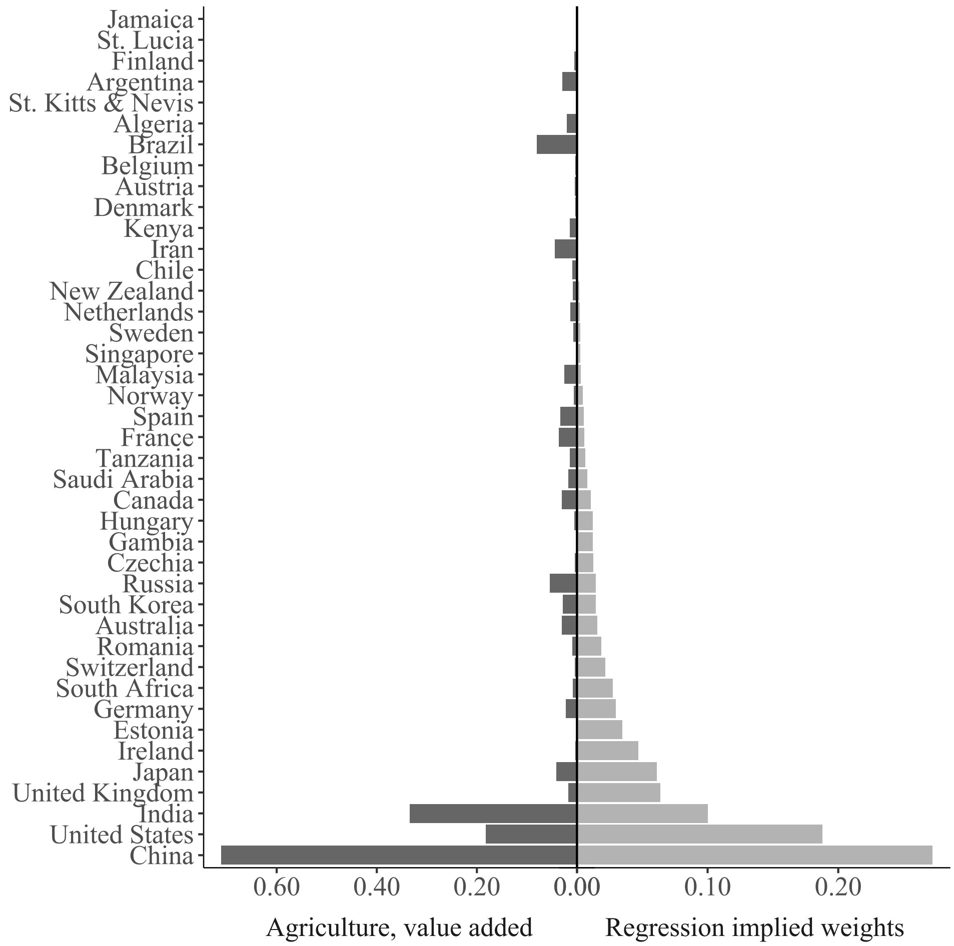

FIGURE B.7: Regression implied weights: agriculture value added.

For the economic value of bovine meat consumption, we note again that the distribution of country weights is not skewed towards countries with large levels of meat consumption (Figure B.8). While Brazil, Argentina, and Australia, all countries with high levels of meat consumption, are assigned high weights, other countries such as Jamaica, Malaysia, and Singapore carry large regression implied weights despite not very beef-heavy diets.

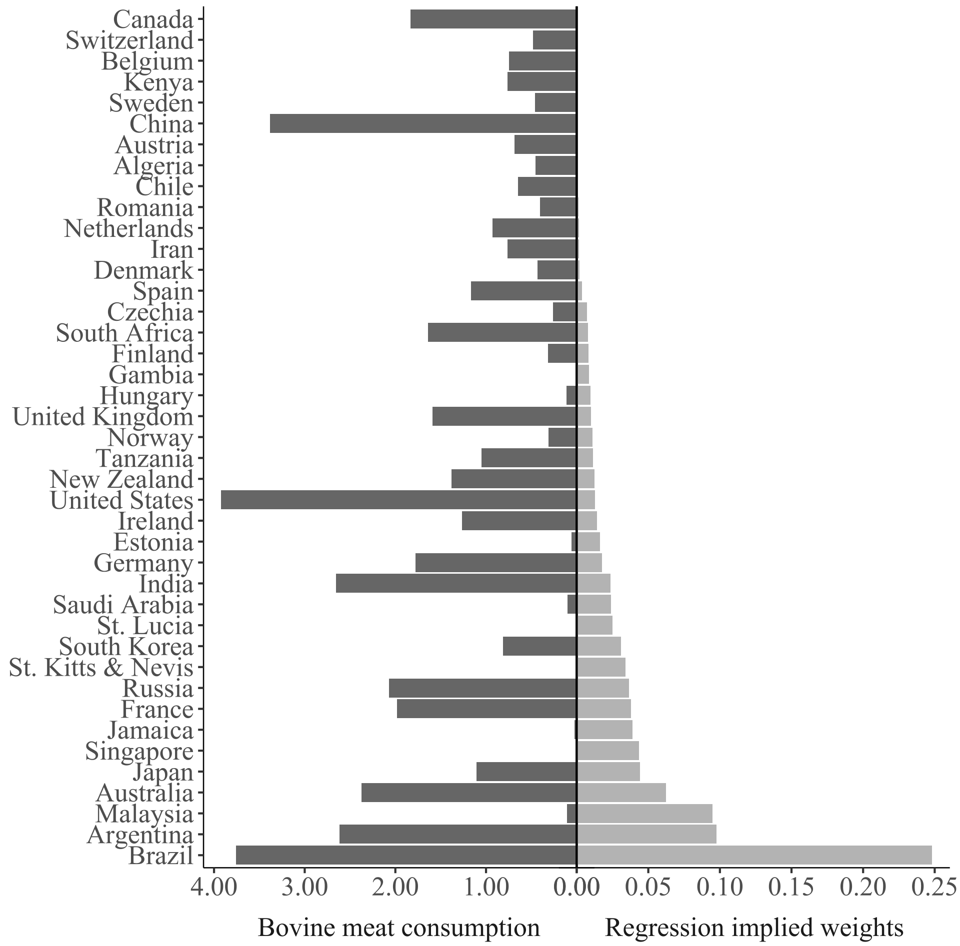

FIGURE B.8: Regression implied weights: economic value of bovine meat consumption.