Government Influence in Information Production in International Organizations[*]

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Abstract

While existing research has extensively studied the conditions under which information can facilitate international cooperation, this paper focuses on the politics of how such information is produced inside international organizations (IOs) in the first place. We develop an argument that models government incentives to seek influence in IO information production as a function of national interests. Focusing on unique data from written government comments on the draft text of the "Summary for Policymakers" flagship report of the Intergovernmental Panel on Climate Change (IPCC), we present two results: first, that governments are more likely to try shape report text when national interests are at stake; and second, that governments comment strategically on exactly those parts of text that are likely to have distributional effects at home. These findings challenge the common assumption that IO information is free from government influence and make us rethink the role of information in global governance.

Keywords: information production; international organizations; distributive politics; climate science; IPCC; government comments.

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Introduction

In global governance, information is essential. Without it, international cooperation becomes protracted, mainly for one of three reasons: either because states lack knowledge about the underlying nature of a cooperation problem; because states lack knowledge about other actors' actions; or because states lack knowledge about other actors' preferences. In all these cases, existing scholarship has shown that information can help facilitate cooperation. Such information, according to most accounts, is typically provided by international organizations (IOs) and their agencies (Keohane, 1984; Milner, 1997; Abbott and Snidal, 1998). IOs help governments, citizens, businesses and other non-state actors observe what is otherwise hardly ever observable. Credible information about a cooperation problem's underlying structure enables more effective governance (Mitchell, 2006) as does making states' actions and interests public. 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 understandings of the exact function that information serves, the international institutions literature shares a broad focus on the "downstream effects" of information. 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 to their audiences. Hence, information production is best conceptualized as the process that generates the contents of the informational outputs that IOs provide, such as reports, data briefings, or press releases.

We develop an argument about government influence in information production, which begins by theorizing that the extent to which states can and do shape the information that IOs produce is governed by institutional rules and political motivations. This recognizes, first, that information production processes vary from one IO to the next as a function of institutional design and, second, that governments have incentives to exercise control over information production in IOs to steer informational downstream effects. Better information and greater transparency are known to constrain government actions (Mitchell, 1994; Dai, 2005; Fang, 2008; Chaudoin, 2014; Hollyer, Rosendorff, and Vreeland, 2015; Kelley and Simmons, 2019), while knowledge about the underlying structure of a cooperation problem can be a powerful resource for structuring and framing international negotiations (Morrow, 1994; Hai, 2024).

Our central idea that governments seek to influence information production in IOs should generalize to a wide range of activities related to information processing inside IOs, including, the sourcing—e.g., police patrol versus fire alarm oversight (McCubbins and Schwartz, 1984; Chaudoin, 2014)—and use—e.g., compliance monitoring versus policy advice (Dai, 2005; Fang and Stone, 2012)—of information. However, the politics of information production that we emphasize will be most relevant (i) when the IO design permits, requires, or encourages country governments' input into information production processes; (ii) when IO-supplied information threatens to be highly damaging or constraining to states; and (iii) when information, once released, is hard to contain. Despite wide potential applicability, we build our main theoretical claims from an analytical setup that fits these scope conditions. We therefore consider cases where IOs act as informational clearing houses that gather, synthesize, and legitimize information to help governments better understand the structural nature of cooperation problems (Abbott and Snidal, 1998; Milner, 1997).

Such information about the state of the world often directly shapes the set of choices governments can make. Therefore, attempting to control information flows when and where they originate can be politically beneficial. Instead of fighting the constraints that information, once released, can impose on governments (for example, by structuring outside options in international bargaining), governments might want to influence IOs' information outputs right at the source. That is, exactly when any constraining content in information outputs is produced inside the IO and, thus, before any IO outputs become public. The successful insistence of governments to *not* being grouped by past emissions and economic wealth in United Nations climate reports, very likely for fear that this would create precedent for emission reduction obligations or financial commitments in annual climate negotiations, is a good example of government influence in information production (Edenhofer and Minx, 2014). Evidence about data irregularities in the World Bank's *Doing Business Report* from 2018 and 2020 as a result of pressure by select country governments, including China, to "adjust" the official business climate rankings adds another insightful case (World Bank, 2021). These examples attest to the power of information in global governance (Doshi, Kelley, and Simmons, 2019) and speak to our logic that governments will often have strong incentives to try shape information at the production stage—albeit with varying degrees of success.

Within a broader conceptual framework of the politics of information production in IOs, we principally argue two points: first, that governments have good reasons to try exercise influence in the production of IOs' information outputs; and, second, that such attempts of government influence can be explained as a function of national interests grounded in domestic politics. Importantly, we neither say that governments' efforts come with guaranteed success nor that government interventions are necessarily ill-intentioned. Most international cooperation problems, especially global ones, are multifaceted. Therefore, countries' exposure to the problem, and the distributional effects from any coordinated action to address it, vary greatly from one country to the next. For some states, attempts to shape the contents of IO reports during information production are hence genuine efforts to ensure that IOs' global information outputs reflect locally nuanced realities. For other states, motivations are more malign and obstructionist. In either case, government incentives to shape information production are rooted in domestic distributive politics. Leaders seek to input into IO information production in ways to preserve national interest and shield potential domestic losers from high cooperation costs. Since the distribution of these adjustment costs are country-specific, our theoretical account recognizes the contextual and sectoral nature of how domestic distributive politics shapes government influence in IO information production. For our empirical analysis of climate change, which is a distinctly distributional problem (Colgan, Green, and Hale, 2021; Aklin and Mildenberger, 2020; Gaikwad, Genovese, and Tingley, 2022; Bolet, Green, and Gonzalez-Eguino, 2024; Hai, 2024), we show that, while fossil fuels are central for explaining attempts to influence IO information production in *some* states, in other countries it is their respective national interests and priorities, covering a wide range from climate vulnerability to land use and food systems, that shape government influence in information production.

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—are highly influential in shaping the discourse in annual climate talks under the UN Framework Convention on Climate Chance (UNFCCC) as they set the scientific guardrails for agreeing a political response to the climate crisis. In keeping with our argument's scope conditions, the IPCC provides governments with structural information about climate change. It is also an ideal test case because member governments are institutionally embedded into the production of IPCC reports both in that they are invited to comment—similar to academic peer review—on a draft version of the SPM and that they negotiate the final SPM text line-by-line. Focusing on unique data in the form of written government comments during the SPM review stage, we use generalized linear regressions to demonstrate that national interests correlate with governments' attempts to influence the information provided in IPCC reports. Importantly, this finding holds not only for countries that are highly dependent on oil production as a dominant structural feature of their economy, but it holds for national interests more broadly. High levels of climate vulnerability, carbon-intensive land use practice, or large beef consumption all increase governments efforts to shape SPM text. Relying on keyword-assisted topic models (Eshima, Imai, and Sasaki, 2024) to validate hand-coded assignments of text sections to particular topics, we provide evidence that governments intervene strategically on exactly those parts of the IPCC text that would have direct implications for domestic interests, such as key national industries.

Our paper makes several contributions. First, it shows that governments will seek to influence information production in IOs if they expect IO-provided information to lead to international cooperation outcomes that would harm domestic interests. This is an important insight because it nuances our understanding of the conditions under which information can credibly facilitate international cooperation. Reminiscent of discussions about whether international treaties screen or constrain (von Stein, 2005; Simmons and Hopkins, 2005), scholars of IOs need to recognize that, more often than not, governments can shape the information production inside IOs and thereby try to limit the downstream effects that IO information can have for constraining government behavior. So far, this possibility has been under-theorized in the international institutions literature when, in practice, many IOs' informational functions rely on government inputs, for instance in the form of data, expertise, finances or staff provided by member governments (Abbott and Snidal, 1998; Nielson and Tierney, 2003; Chwieroth, 2013; Clark and Dolan, 2021; Voeten, 2021; Clark and Zucker, 2024). In all these cases, IO information is likely to reflect government interests at least to some extent. Moreover, government influence in information production may be a much lesser issue when the institutional rules empower IOs to protect information production processes from government influence, emphasizing aspects of institutional design (Abbott and Snidal, 1998; Koremenos, Lipson, and Snidal, 2001; Johnson and Urpelainen, 2014).

A second implication of our argument for future research is that the power of IOs for facilitating international cooperation, in highly technical areas that depend on specialist government expertise, may be more limited than previously thought. Issues such as cyber security, cryptocurrencies, antimicrobial resistance, artificial intelligence, or climate change all require considerable informational input from states, potentially constraining the extent to which IOs can be shielded 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 information production processes in IOs and contribute to the growing use of text-as-data approaches in international relations (e.g., Chaudoin, 2022; Thrall, 2023; Kennard, 2023).

Finally, our research speaks to the existing literature that puts domestic distributional conflict at the core of climate politics (Colgan, Green, and Hale, 2021; Aklin and Mildenberger, 2020; Bayer and Genovese, 2020). 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 publics, 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 the international negotiations themselves, but also apply to information production processes that *precede* these actual negotiations over cooperation outcomes. From a normative perspective, these findings challenge the assumption that information production in IOs is free from politics and 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

International cooperation fails for many reasons, but the lack of knowledge about a cooperation problem's underlying structure is chief among them. Without a clear sense about the state of the world, coordinating state behavior becomes difficult. Governments will find it hard to even know what constitutes an adequate global governance response (Mitchell, 2006), and the politicization of uncertainty further complicates cooperation (Hai, 2024). 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). International organizations therefore function as informational clearing houses. They collect, vet, and disseminate information. In doing so, they effectively change what governments know about central aspects of any given cooperation problem. This reduces the likelihood that government coordination breaks down over a lack of shared understanding of what the "true" state of the world looks like.

Many IOs across virtually all issue areas of international cooperation provide information about the state of the world as part of their core informational 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 this type of 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 and information production process that requires consensus and compromise by design (Mitchell, 1994; Fortna, 2003; Fang, 2008). As a result, much of the international cooperation literature tacitly assumes that IO information is free of government influence and largely exogenous to states' national interests.

While this notion of IOs as unbiased information providers comes with intuitive appeal, it sits somewhat uncomfortably with two other observations from international institutions research. First, for most IOs to fulfill their information functions, they rely considerably on country-specific knowledge, data, and expertise to be passed on freely between national governments and IOs (Abbott and Snidal, 1998; Nielson and Tierney, 2003; Voeten, 2021). Governments therefore control when, how, and to what extent national informational inputs feed into information production in IOs. Evidence that autocrats (Hollyer, Rosendorff, and Vreeland, 2018, 2011) and populist leaders (Carnegie, Clark, and Zucker, 2024) can throttle and restrict information flows to IOs strongly suggests that, at least in some cases, IO information does reflect states' interests. 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 this logic, but turning our analytical focus from decision-making outcomes to information production, 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 outputs of IOs whenever this can mitigate undesirable downstream effects. Second, we claim that the way in which governments do so is a function of national interests.

We begin by recognizing the role of information for international cooperation. In settings like ours, where IOs provide information about the true state of the world, any information that reveals key structural aspects of the underlying cooperation problem will likely affect 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 can compel governments towards greater cooperation because 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*). In the example of ozone depletion, once scientists had discovered that chlorofluorocarbons are at the heart of the problem, this knowledge about the physical state of the world prodded policymakers into action (Haas, 1992*a*; Benedick, 1998). Even for climate change, an issue of larger scale and with many more reasons complicating international cooperation (Bernauer, 2013), scientific evidence—e.g. presented in the IPCC's 1.5°C Special Report—increased pressure on governments to become more ambitious about decarbonization.

IO information can therefore limit, or at least challenge, governments' actions.[1] It might make states adopt policies they would not have adopted otherwise. Since implementing these policies is costly as they typically come in the form of greater cooperation commitments, one way for governments to avoid these costs is by trying to shape the contents of the information that IOs provide in the first place. Attempts of molding IO information at the production stage to align international responses to cooperation problems with national priorities can be a subtle, yet effective approach to minimize downstream effects of IO information. Importantly, this does not mean that governments' efforts to shape IO outputs are necessarily ill-intentioned interference. In fact, governments can have good reasons for feeding their national views and priorities into IO information production and associated reports, especially in those cases where the global nature of many IO assessments risks overlooking nuance and variation at local and regional levels.

Whatever motivation—and our theory is deliberately agnostic here—governments may have to seek influence in IO information production, trying to do so is appealing because it is often easier for governments to control the contents of IO information outputs than to navigate informational downstream effects. From a simple temporal perspective alone, information production happens

[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).

strictly before the publication of any IO output. This is why, through interventions during the production stage, governments are able to plant their priorities and interests into IO outputs right at the source—i.e., exactly when IOs create the relevant information that will ultimately define the true state of the world. This logic echoes work by Kennard (2023) about far-sighted bargaining, with the difference that, in her case, it is international regimes that endogenize the status quo of otherwise ad-hoc negotiations whereas, for us, it is prior information production (instead of prior bargaining outcomes) that creates downstream realities for governments.

Apart from arguing that governments have incentives to shape information production in IOs, we also claim that they do so with a view towards national interests. This point follows rather directly from combining our theoretical framework's emphasis on 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 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 across many democracies, such distributional pressures receive increased attention (De Vries, Hobolt, and 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, governments can, so we argue, reduce pressures to even having to confront distributional effects from deeper cooperation by seeking influence in IO information production.

Protecting salient domestic interests through information production only becomes possible because scientific evidence, which we assume much IO information relies on, is multifaceted, complex, and needs to be translated from academic findings into policy recommendations. That is why governments will be able to interpret and portray the same scientific evidence differently and in ways that gel with national priorities (Allan, 2017). For IO information production this practically means that governments have enough latitude to try and feed their own interpretation of scientific evidence into IO-created outputs with the intention of changing the distributional effects that IO information creates downstream.

Governments can do so by attempting to create rents and deflect 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 the same 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 widespread reliance of IOs on government inputs ensures that government principals have access to information production in IOs. While the scope for governments to shape IO outputs is clearly greatest when institutional rules are permissive and invite, or even require, government participation in information production, unless information production is completely firewalled, IOs depend on member governments for access to data and expertise, financial support, staff, and because of institutionally required consultation or approval processes (Abbott and Snidal, 1998; Nielson and Tierney, 2003; Chwieroth, 2013; Clark and Dolan, 2021; Voeten, 2021; Clark and Zucker, 2024).

In all these cases, the politics of information production matter, and governments have incentives to create cooperation winners and protect cooperation losers by means of shaping information outputs inside IOs. No matter which of the two motivates governments more, the key observable implication of our argument is that *governments will intervene in IO information production in a way that is consistent with preserving national interests*. When applying this expectation to international climate cooperation, where national interests are simultaneously country- and sector-specific, our argument can most compellingly be tested with an empirical case that allows us to leverage contextual variation in what constitutes 'national interest.'

Background on the IPCC

The Intergovernmental Panel on Climate Change (IPCC), the UN system's main body on climate science, offers just such a case. Founded in 1988 by the World Meteorological Organization and the United Nations Environment Programme, the IPCC is 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 several reports at the end of a 5–7-year long assessment cycle. These IPCC products come in the form of an underlying report of normally 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] As the IPCC's main information outputs, the reports matter because they feed scientific evidence into annual UNFCCC meetings (Hai, 2024), where negotiated outcomes can create downstream 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

[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/.

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 are deliberately permissive. They were designed consciously in such a way as to facilitate ownership of and shared responsibility for any of the IPCC-produced reports among member governments (de Pryck and Hulme, 2022). An institutional design like this—as premised by our theory—creates opportunities for governments to shape the contents of IPCC reports and is hence ideal for testing our argument empirically. We focus our data analysis on the *review stage* of the SPM writing process as the first of two salient points in IPCC information production where governments can directly shape the language used in the SPM. They do so by submitting written comments to report authors requesting edits, additions, or deletions to the report text, which authors can then accept or reject. The SPM text typically changes considerably as a result of government comments, making 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 (WHO) annual World Health Report to the World Trade Organization's (WTO) 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,

[3] The SPM of Working Group III of the latest Sixth Assessment Report (April 2022), for example, saw 17 pages added as track changes, increasing the SPM's total word count from 17,359 words to 22,212 words. Fairly low measures of text similarity, such as a Levenshtein similarity of 0.51 and cosine similarity of 0.75 (based on term frequency-inverse document frequency, TF-IDF), offer descriptive evidence that review comments changed the textual representation of the language in the SPM across versions.

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. For the latest Working Group III Summary for Policymakers on climate change mitigation options, which was published in April 2022 and is the focus of our empirical analysis, a total of 42 governments submitted 4,954 comments overall, contained in a 576 pages-long document. In response to a draft text of 43 pages in length, this amounts to an average of roughly 115 comments per page. Basic data like these are indicative of the importance that governments attach to information production in the IPCC and the value they see in attempting to shape the contents and language in SPM documents.

Research Design and Empirical Strategy

For our empirical analysis, we rely on the complete set of 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 offer a detailed account of government efforts to shape information production in an IO. They are a unique resource for our analysis because, compared to other IOs where governments influence information outputs behind closed doors, attempts to change SPM text during the IPCC's review stage are observable to researchers and are documented in writing.

Our analysis provides 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 preserving national interests as the central motivation for governments to shape information production extends beyond oil. Indeed, dependence on other climate-forcing assets or high levels of climate vulnerability as alternative markers for national interest equally translate into government activity to shape IPCC outputs. Conforming to our theory, governments do not request textual changes in an indiscriminatory fashion, but intervene specifically on those parts of SPM text that have relevant implications for their corresponding national interests and policy priorities at home. We therefore offer combined evidence for our main expectation that governments will intervene in IO information production as a function of national interests that recognize the domestic distributive consequences of greater international climate cooperation.

Measuring Government Efforts to Shape SPM Text

The IPCC's institutional design allows measuring otherwise difficult-to-observe efforts by governments to influence information production in IOs. We do so by using the official record of 4,954 written review comments that 43 government delegations submit to the IPCC requesting changes to the SPM draft text. Since comments are intended to effect changes to the SPM text, they are a good operationalization of efforts to influence information production in the IPCC. 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 part of the text.[4]

Excluding the introduction, which primarily contextualizes and outlines the report, the SPM draft for WGIII in AR6 comprised 40 of what we call "parts of text" (POTs). We define these POTs as self-contained textual, visual (e.g., figures), or numerical (e.g., tables) blocks of information on specific aspects of mitigation policies. They follow quite naturally from the SPM text's hierarchical structure, which is divided in headline statements—referenced as 'B.1', 'B.2', . . . 'C.1', 'C.2', and so forth—that include supporting scientific evidence in lower-order paragraphs—e.g., 'B.1.1', 'B.1.2', and 'B.1.3' back up claims made in statement 'B.1'.[5] We link submitted comments to specific POTs using information about the page and line of the draft text which the comment refers to. 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),

[4] As part of the data cleaning process, the 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 a large number of government comments, we treat each figure and table as a POT of their own rather than assigning them to the POT of the paragraph in which the figures and tables appear in. The SPM draft we analyze has 11 figures and one table.

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 strategy for it allows the inclusion of POT-level fixed effects in our regression models below and the analysis of topic-level variation as different POTs relate to different topics in climate mitigation.

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

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.

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 the request for any changes to SPM draft text. Full set of comments N = 4,347.

Figure 2 shows the number of submitted comments for the 25 governments that submitted the most comments overall, alongside the respective distributions for the number of comments submitted for POTs that focus specifically on carbon, capture and storage (CCS) technology and POTs related to emissions from agriculture, forestry, and land use (AFOLU). These data provide initial evidence that national interests tied to oil production, for example through direct exploration or headquartering large oil multinationals—as is true for the US, France, the UK, Germany, Saudi Arabia, Norway, India, and Canada—, matter for the number of submitted comments. National interests are, however, multidimensional and hence not always 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.

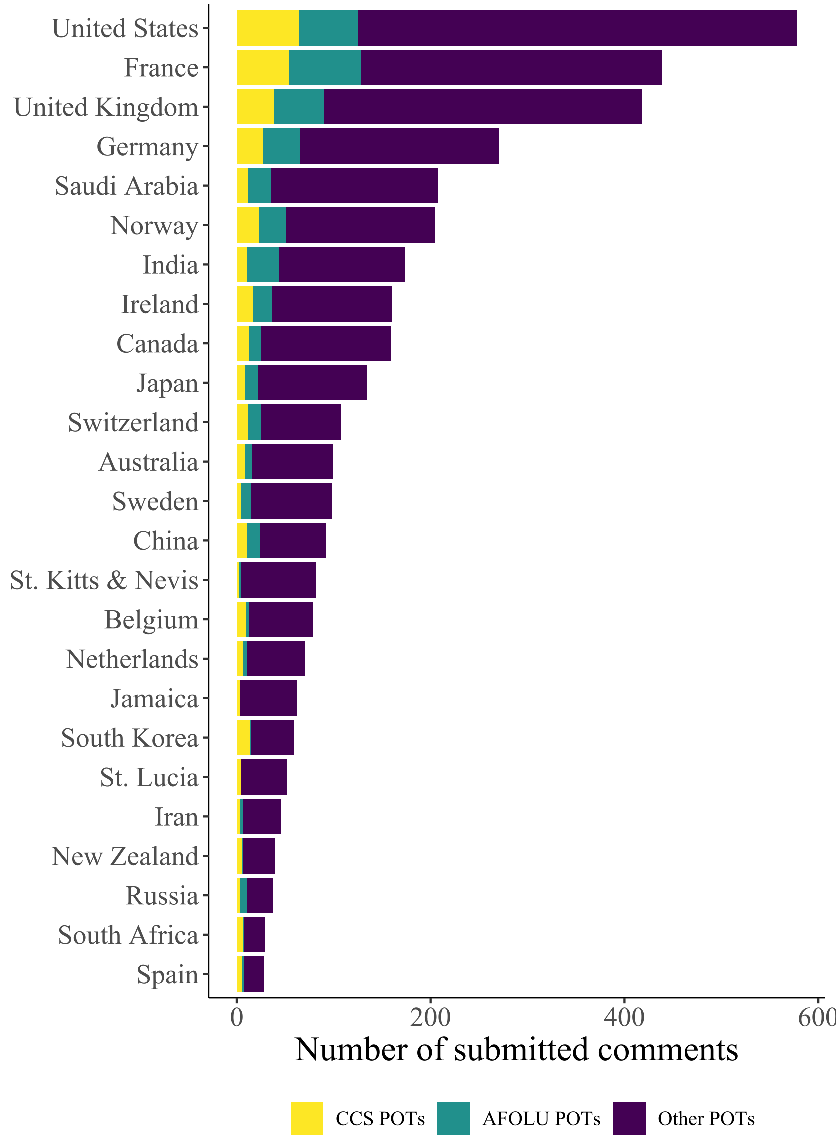

FIGURE 2: Number of government comments by country and topic for WGIII SPM draft text. We plot the top-25 countries with the largest number of overall comments.

For our regression analysis, we create a count and a binary variable from the official IPCC record of government-submitted comments as our two outcome measures to get at both intensive and extensive margins of government effort. Using granular information about the exact part of text (POT) a government comment refers to, our count variable measures the number of comments a government submits to *each* of the 40 well-identified POTs in the SPM. The binary outcome variable, as our second measure, captures whether a government commented at least once or not at all on each of the individual POTs. 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); indeed, four out of ten countries do not comment on an average POT. Governments do therefore not comment on all parts of the SPM equally, but target their efforts—as we show below, even after controlling for variation in countries' scientific capacity and involvement with the IPCC—on POTs that matter the most for their national constituencies in terms of distributional consequences.

Measuring National Interest

As articulated above, national interest is multi-faceted and varies across contexts: what is a key political priority in one country matters much less elsewhere. This logic applies to distributional effects of international climate policy as well. Countries assess the consequences of climate policy differently depending on, for example, the industrial composition of their economies or their vulnerability to extreme climate events. Our theory argues that these differences matter. They do so because they structure national interests which motivate governments to shape information production in IOs. We respond to the complexity of how to best operationalize national interest in our empirical analysis with a nuanced approach that relies on five separate measures to capture a wide array of different aspects of national interest in international climate politics.

The first variable we use proxies states' oil dependence on the production side through country-level, per capita measures of oil capital. This "topline" indicator recognizes the structural embeddedness of oil in advanced economies. Considering the outsized role of fossil fuel interests in climate politics (e.g., Falkner, 2008; Bernauer, 2013; Stokes, 2020; Mildenberger, 2020; Colgan, Green, and Hale, 2021), we expect oil dependence to fundamentally shape government interventions in IPCC report production.

We also use four additional measures to capture other important dimensions of how national interests structure government responses in IPCC information production. The first one measures 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. These 39 highly climate vulnerable countries, including Jamaica, Fiji, St. Lucia and the likes, face an existential threat from global warming, which 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 a country's value added to its economic output from industrial production, which includes manufacturing, mining, construction, and electricity production as key (and carbon-intensive) sectors, and—as a separate measure—value added to the national economy's output from agriculture, forestry, and fishing. Both industrial and land use emissions, as captured by these two variables, are 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 five distinct measures helps us empirically characterize the multidimensional nature of national interest and how it relates to climate politics and IPCC information production in multiple ways. We logarithmize all variables (except for the SIDS dummy) to reduce their distributional skew and to account for diminishing returns, and show in Appendix B.2 that these transformations are not driving our results. We describe variables and their sources in Tables A.1 and A.2.

Control Variables

For our selection on observables design, we include several control variables 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 pollutive 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 minimize spurious correlation that most certainly arises from cross-country differences in research power and variation in countries' familiarity with and capacity to productively engage in IPCC processes. To do so, 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 or not. We average covariates over the years from 2015 to 2021, which mark the start of the assessment cycle and the SPM review, respectively, to smoothen over-time trends and to ensure that covariates are measured pre-treatment.

Topic-Level Analysis

We strengthen the credibility of our empirical analysis through topic-level tests. The core inferential idea here is simple. If national interest, indeed, motivates governments to seek influence in IPCC text production, governments should primarily comment on those parts of text that are particularly relevant to protect or advance exactly these types of interest. We implement this logic by interacting our above measures of climate vulnerability, industry value added, agriculture value added, and beef consumption with SPM parts of text that speak specifically to these interests.

For this, we focus on two topics: carbon capture and storage (CCS) and agriculture, forestry, and other land use (AFOLU), both of which were central discussion points in the Sixth Assessment Report—and will continue to be so going forward. For both topics, we identify POTs in the SPM that summarize the scientific evidence base specific to CCS and AFOLU.[6] CCS, as a technology

[6] We define both topics in broad terms rather than narrowly. Our CCS topic therefore includes references to re-

that allows capturing and permanently storing CO_2 underground, is important for mitigating emissions from hard-to-abate sectors like cement and steel. It is also critical for balancing residual emissions mid-century to achieve net-zero targets (Ganti et al., 2024). Skeptics, however, fear that it deters decarbonization and locks in the use of fossil fuels in the long run (Anderson and Peters, 2016; Fuss et al., 2014). As a topic, it is ideal for our analysis because both advanced economies with high levels of industrial emissions and highly climate vulnerable countries have been shown to be vocal about the deployment of CCS and related technologies, albeit for opposing reasons (Bayer et al., 2025).

Our second topic of AFOLU relates to emissions from agriculture, forestry, and land use as large contributors to countries' terrestrial greenhouse gas (GHG) emissions. For large forest nations, such as Brazil and Indonesia for example, emissions from these sources can easily make up almost half of their total annual GHG output. Standing forests are also often subject to deforestation pressures for agricultural use, either for high value crops or meat production. For us, this creates a useful link between AFOLU as a topic in the SPM and two of the measures we use to operationalize national interest (i.e., value added from agriculture and bovine meat consumption).

Based on a qualitative coding of topics in SPM parts of text, we identify POTs B.4, C.5, and C.11 as relevant sections in the SPM that focus on CCS. We classify POTs C.6, C.9, D.1, and D.2 as related to AFOLU.[7] For our regression analysis, we create two binary variables that each score 1 for POTs that cover CCS or AFOLU as the main topic, respectively. Appendix B.6 demonstrates that our results are robust to using a semi-supervised topic model for classifying topics (Eshima, Imai, and Sasaki, 2024) instead of assigning POTs to topics manually.

lated 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 on land use, land use change, and forestry (LULUCF).

[7] POTs that refer to CCS and AFOLU received 391 comments (9% of total) and 448 comments (10% of total), respectively (Figure A.1). This ensures that the two topics we identified for conditioning the main estimates of national interest on received proportionate coverage in terms overall comments.

Model Specification

We estimate two sets of models, one with a count and the other with a binary dependent variable. For the count specifications, we use Poisson regressions and remove any variation across POTs from, for example, differences in topic, length, technicality, or imprecision in the reported content with POT-level fixed effects. These models explain government attempts to shape SPM contents—through submitting comments to the IPCC—from within-POT variation as a function of national interest (measured as oil dependence) and covariates, before averaging estimated effects across POTs. Specifically, our estimation equation is

$$\textsc{comments (count)}_{cp} = \alpha_p + \delta \times \textsc{interest (oil)}_c + \mathbf{X_c}\boldsymbol{\beta} + \varepsilon_{cp}, \tag{1}$$

where $\textsc{comments (count)}_{cp}$ denotes the *number* of comments submitted by government c on POT p, $\textsc{interest (oil)}_c$ captures national interest, operationalized here as oil dependence, $\mathbf{X_c}$ is a matrix of country-level covariates, discussed above, and α_p is a POT-level fixed effect. Standard errors are two-way clustered by country and POT.

We expect a positive estimate for the δ parameter. Within our theoretical framework, this means that greater national interest in the downstream effects of information that the IPCC provides through its reports translates into a greater number of comments that governments submit 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.

Our second set of models uses a binary dependent variable of whether governments comment on a given part of SPM text (=1) or not (=0). We estimate these as logistic regressions and model governments' attempts to exercise influence on text production as the conditional effect of different operationalizations of national interest and topic dummies. The estimation equation reads

$$\text{COMMENTS (0/1)}_{cp} = \alpha_p + \gamma\text{INTEREST}_c + \phi\text{TOPIC}_p + \delta\text{INTEREST}_c \times \text{TOPIC}_p + \mathbf{X_c}\boldsymbol{\beta} + \varepsilon_{cp}, \quad (2)$$

where we interact the above discussed SIDS and industry value added measures with our CCS topic indicator and the agriculture value added and beef consumption measures with the AFOLU topic dummy, respectively. We expect a positive δ parameter on the interaction term, which indicates that governments comment *specifically* on those POTs that very likely hold distributional consequences for their national constituencies. Our preferred specifications do not include POT-level fixed effects to our logistic interaction models for a clearer interpretation of the identifying variation across country-level and text-level features. To address concerns that this approach necessitates stronger conditional independence assumptions for model identification, we demonstrate that parameter estimates are almost identical across specifications with and without POT-level fixed effects.

Results

We report empirical results in two steps. First, we show the topline finding from our count models that countries whose national interests are structurally tied to oil production submit an overall far greater average *number* of comments to the IPCC across all POTs. Second, and looking beyond the intensity of government effort, we demonstrate that governments are strategic in their commenting behavior: evidence from our logistic regressions, which allow us to test what *types* of POTs and, hence, what specific topics governments comment on, rather than how much they comment overall, strongly support this claim.

Count Model Results: Intensity of Government Effort

Table 1 presents several models, ranging from a parsimonious specification to avoid suppression effects (Lenz and Sahn, 2021) to ones 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 for the average POT of the draft SPM text. In estimating these effects, which are all statistically significant and increasing in size when relevant controls are added, any form of confounding due to the very topic discussed in a given POT is completely absorbed thanks to the inclusion of POT-level fixed effects.

The estimated effects are substantively large. For model (1), which produces the smallest point estimate across all our specifications, an increase in per capita oil capital of one standard deviation (+1.18) over its average (0.74) increases the number of government-submitted comments by 1.24 [0.33, 2.15], or by roughly a third of the mean. This positive relationship holds for the full range of the oil capital variable as shown in Figure 3. 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. More specifically, 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 empirical distribution (shown as the dashed line in our 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 of the SPM.

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.[8] Figure 4 (left panel) shows that for the three

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

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
R^2	0.140	0.205	0.385	0.432
R^2 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.

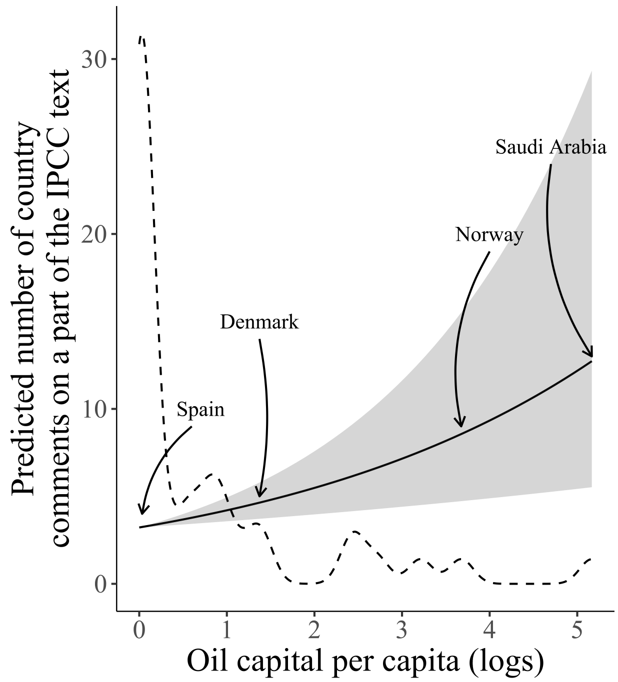

FIGURE 3: Number of government-submitted review comments as a function of countries' oil capital per capita. Predicted counts are shown as black line with 95% confidence interval in gray, based on model (1) from Table 1. The dashed line shows the empirical distribution of the logged oil capital per capita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

most predictive covariates from model (4) above, the effect of oil capital gets estimated as 0.25 for a confounder that is 10× as strong as the natural resources availability variable, as 0.36 for a confounder that is 10× as strong as the GDP variable, and as 0.34 for a confounder that is 10× as strong as the *Nature* research leader index variable, respectively. Even hypothesizing such extreme forms of confounding, the obtained point estimates would remain substantively large (comparable in size to the reported effect from model (1), which we used to illustrate substantive effects in Figure 3); they would also largely retain statistical significance (except for a confounder 10× as strong as the Natural Resources variable, for which our estimate-of-interest would fall short of 0.05 significance level). This evidence provides compelling support for our theoretical expectation that national interest connected to oil production shapes governments' attempts to influence SPM text and that, at the same time, our identifying conditional independence assumption very plausibly holds.

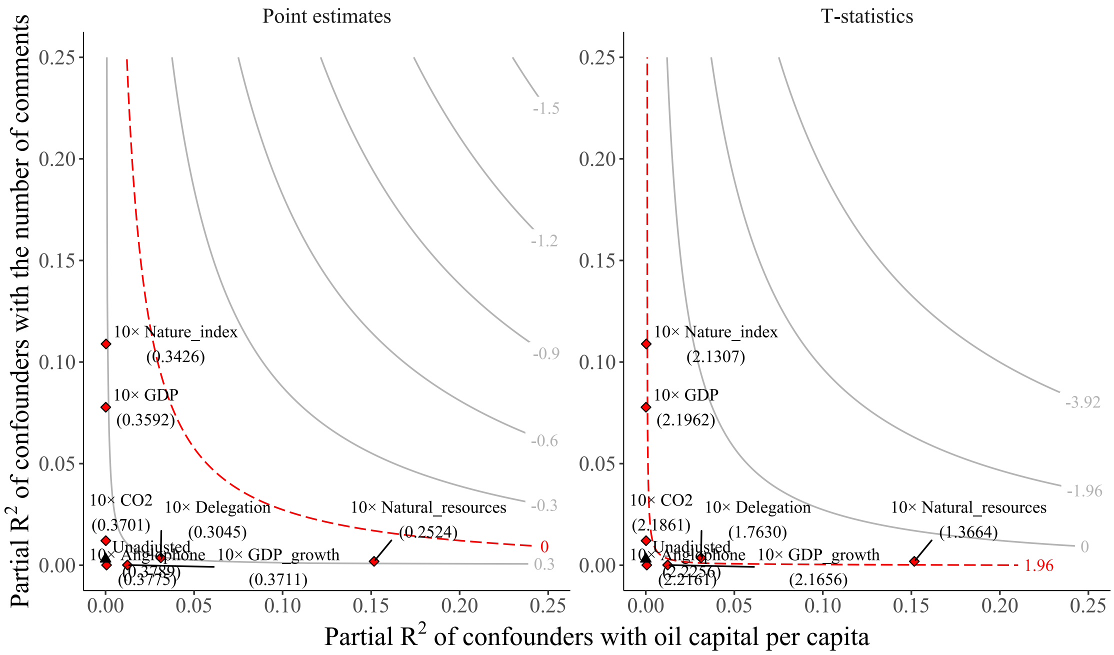

FIGURE 4: Results of sensitivity analysis. Following Cinelli and Hazlett (2020), we show that the effect of oil capital per capita on the number of government-submitted comments on SPM parts of text remains positive and significant even in the presence of a large unobserved confounder. Results for point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

Logistic Regression Results: Topic-Specific Government Effort

Our second set of results demonstrates that governments seek influence in IPCC report production for many other forms of national interest, too, that are unrelated to oil. We show in particular that governments comment *strategically* on topics that matter to their domestic constituencies, as captured by a positive interaction term between measures of national interest and topic dummies for CCS and AFOLU. Table 2 presents evidence from a total of 12 models, comprised of three specifications for each of our four distinct operationalizations of national interest. Apart from national interest shaped by high levels of climate vulnerability in the case of SIDS countries (models 1–3) and carbon-intensive industrial production (models 4–6), we also account for interests tied to agricultural production (models 7–9) and beef consumption (models 10–12). Model specifications are differentiated by the extent to which they include control variables and POT-level fixed effects.

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)
Climate policy exposure	-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)
Climate policy exposure × 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)						
Climate policy exposure × 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]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'.

Consistent with expectations, we find that, across all models, the likelihood for governments to try and shape SPM text increases only as a *combination*—statistically speaking the interaction—of national interest and those parts of text that relate to distributionally relevant topics. For small island states and countries with high levels of industrial production this is the case for POTs that refer to carbon capture and storage technology. For countries with large agricultural production and heavy beef consumption, this is the case for POTs summarizing scientific evidence on agriculture and land use emissions. The fact that commenting behavior at the *topic level* aligns with countries' national interests is compelling support for our argument. We strengthen this claim about strategic government behavior even further by showing that there is no evidence that measures of national interest—independent of how it is operationalized—would, by themselves, increase the probability for governments to submit comments to the IPCC. The constituent terms of almost all national interest variables (except for industry value added) are estimated imprecisely and several of them even flip signs across models. However, national interest does have exactly the expected positive interaction effect whenever a part of SPM text relates to a topic that has substantial material consequences for domestic audiences.

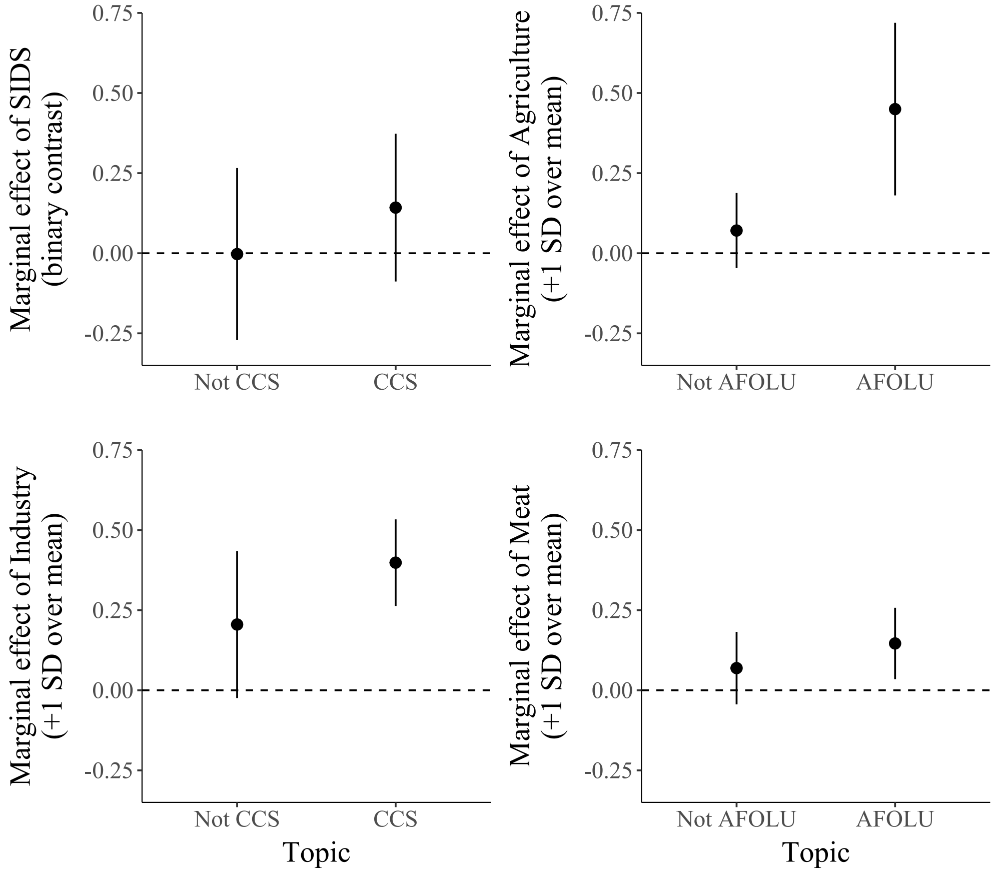

FIGURE 5: Marginal effect of national interest on probability to submit comments on SPM parts of text. Plots show marginal effects and 95% confidence intervals from models (1), (4), (7), and (10) in Table 2 when changing all four measures of national interest from the mean to one standard deviation (+1 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'.

To facilitate the substantive interpretation of the estimated interactions, we compute marginal effects from models (1), (4), (7), and (10) in Table 2 when changing all four measures of national interest from their mean to one standard deviation above the mean (+1 SD), with the exception of the SIDS variable for which we use a binary SIDS versus non-SIDS contrast. Figure 5 breaks marginal effects out by parts of text that focus on CCS technology and those that do not (left panels) as well as by POTs dealing with agriculture and land use (AFOLU) emissions and those that do not (right panel). We find that point estimates of marginal effects for all four national interest measures are larger when we condition on the (distributionally) relevant part of text than what we observe for any other POT. Effects for national interest captured through economic fundamentals, as measured in terms of relative industrial and agricultural composition, are similar in size and move predicted probabilities for a government to comment on a CCS or AFOLU POT, respectively, by about 40 percentage points. Effect sizes for national interest, as proxied through being classified as a SIDS state and beef consumption, are smaller and amount to a 15 percentage point shift in the predicted probability to comment. Findings for SIDS are not estimated tightly enough to pass standard tests of statistical significance, possibly due to increased variance in our measure as small island states often coordinate their contributions as a group through designated 'spokescountries' or lack of capacity to engage with IPCC proceedings.

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 dependence 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 on parts of text at all. Next, we conduct placebo tests to probe our argument that oil dependence structures attempts to interfere with IO-produced climate science in general, whereas other forms of national interest only produce effects that are conditional on topics (Appendix B.5). In our main analysis, we identify POTs that relate to CCS and AFOLU through qualitative coding of POT contents, 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 thus helps coordinate government action (Abbott and Snidal, 1998; Mitchell, 2006; Voeten, 2021). Much of this logic, however, rests on the assumption that information provided by IOs is exogenous and largely independent of government influence. In this paper, we challenge this notion by arguing that information production in IOs is often itself a political process that is subject to power, interests, and government influence.

There is little doubt that governments have strong incentives to shape the contents of IO reports, IO-published country rankings, and other influential IO information outputs if governments have the chance to do so. Given the wide reach of many IOs to share information with other governments, non-governmental actors, and domestic publics, being able to exercise influence over information production inside IOs is politically desirable. Governments that manage, at the point of writing, to shape the contents of IO reports in ways to align these information products with national interests can effectively shield themselves from the downstream effects of information.

We therefore argue and empirically show that governments do indeed intervene in the production of the "Summary for Policymakers" (SPM) of the latest key report on climate mitigation policy of the IPCC, the UN's preeminent body on climate science. Building on unique data in the form of written review comments that governments submitted to the IPCC authors, we demonstrate that national interest predicts governments' attempts to shape SPM text. This is true for countries whose national interest is tied to oil production, yet the pattern holds more broadly: states with national interests derived from high levels of climate vulnerability, economic dependence on industrial manufacturing or agricultural production, and beef consumption are all more active in attempting to change SPM text. We find support for our argument when it comes to the number of submitted comments but also for the specific location of text that a comment refers to. Governments comment strategically on exactly those parts of text that matter the most to their domestic constituencies. These results connect well with the body of work that highlights the distributional nature of climate politics (Colgan, Green, and Hale, 2021; Aklin and Mildenberger, 2020; Bayer and Genovese, 2020; Gaikwad, Genovese, and Tingley, 2022; Gazmararian and Tingley, 2023; Bolet, Green, and Gonzalez-Eguino, 2024) to which we add a distinct observation: Domestic distributive politics matters for international cooperation at a much earlier stage than what has typically been assumed by most scholarship to date. In what we see as this paper's main contribution, we show that states' national interests matter already during information production in IOs rather than only during negotiations over 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 will have been influenced by government interests to a much greater extent than what informational theories of cooperation suggest. Recognizing, as our argument does, that IO information is not neutral, objective, and free from government influence at all times should prompt future research into at least three directions.

First, by conceptualizing information production in IOs as a central (and endogenous) part in institutionalist frameworks of international cooperation, we can develop a more nuanced 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 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 information production holds profound consequences for political scientists' 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
CO2 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	
CO2 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	Hand-coded		

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
CO2 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

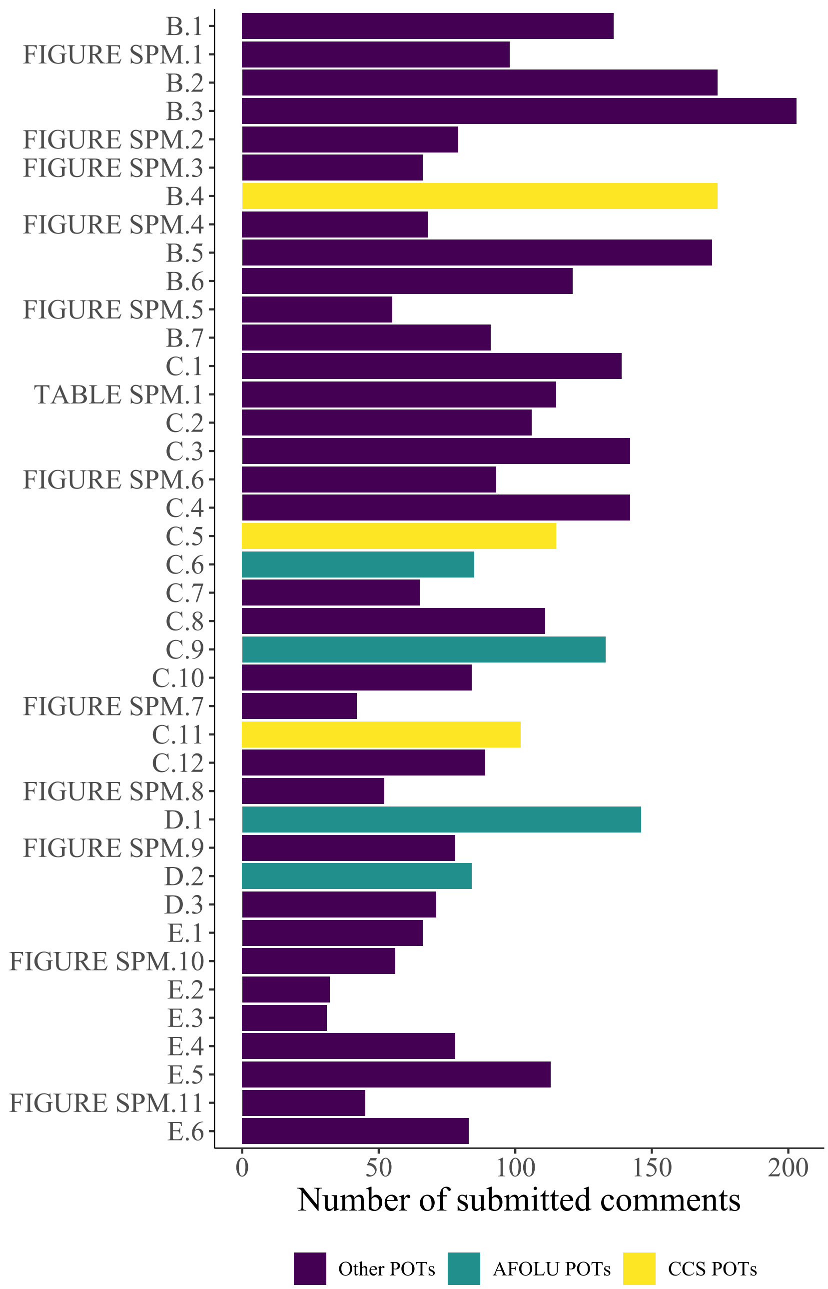

FIGURE A.1: Number of government comments by POT of the WGIII SPM draft text.

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)
Climate policy exposure	-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)
Climate policy exposure × 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)						
Climate policy exposure × 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)	
CO2 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]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.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 (log)	0.009***	0.013***	0.019+	0.019*
	(0.002)	(0.002)	(0.010)	(0.009)
CO2 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 × 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 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	-0.011	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)
Climate policy exposure × 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)						
Climate policy exposure × 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]Climate policy exposure: Membership in the "Small Islands Developing States" (binary). Source: UN

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

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

[4]Climate policy exposure: 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)
CO2 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 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	-0.003	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)
Climate policy exposure × 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)						
Climate policy exposure × 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]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 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 dependence 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)
CO2 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 × 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 climate policy exposure 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)
Climate policy exposure	-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)
Climate policy exposure × 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)						
Climate policy exposure × 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]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 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)
Climate policy exposure	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]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.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.

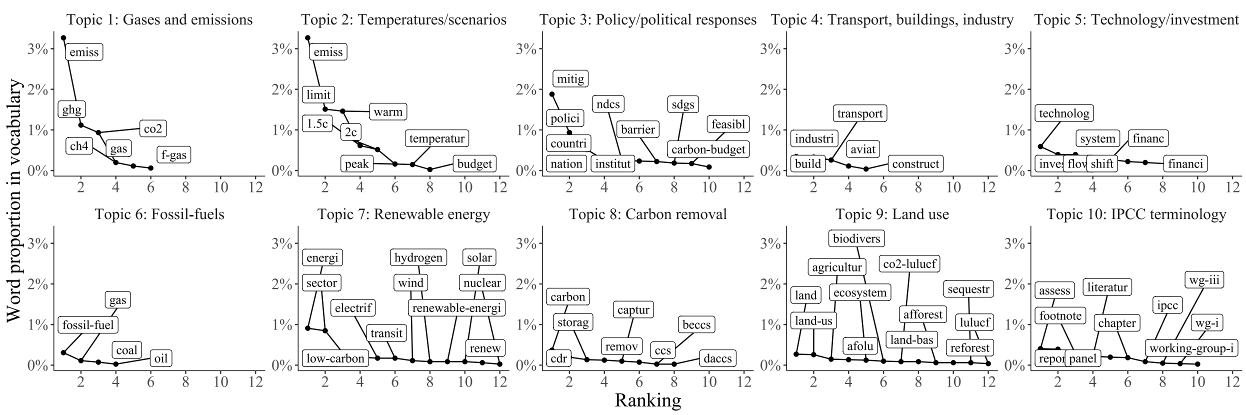

FIGURE B.1: Frequency of keywords for the ten labeled topics supplied to keyATM.

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.

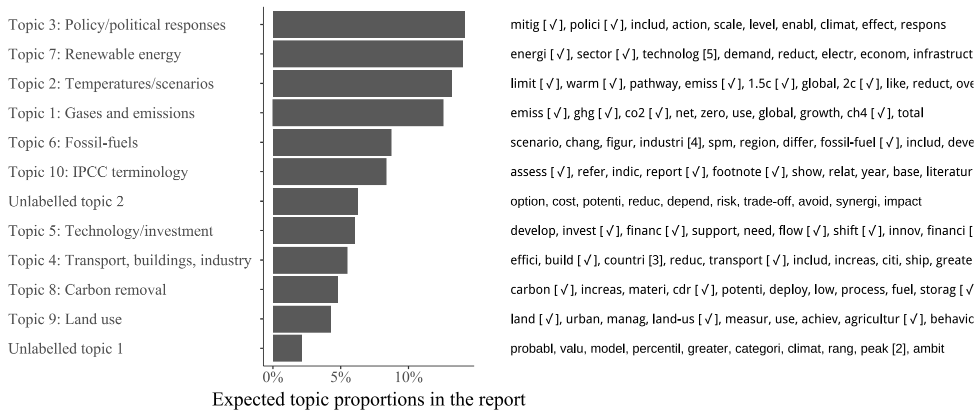

FIGURE B.2: Frequency of predicted topics from keyATM with top-10 words for each topic.

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.

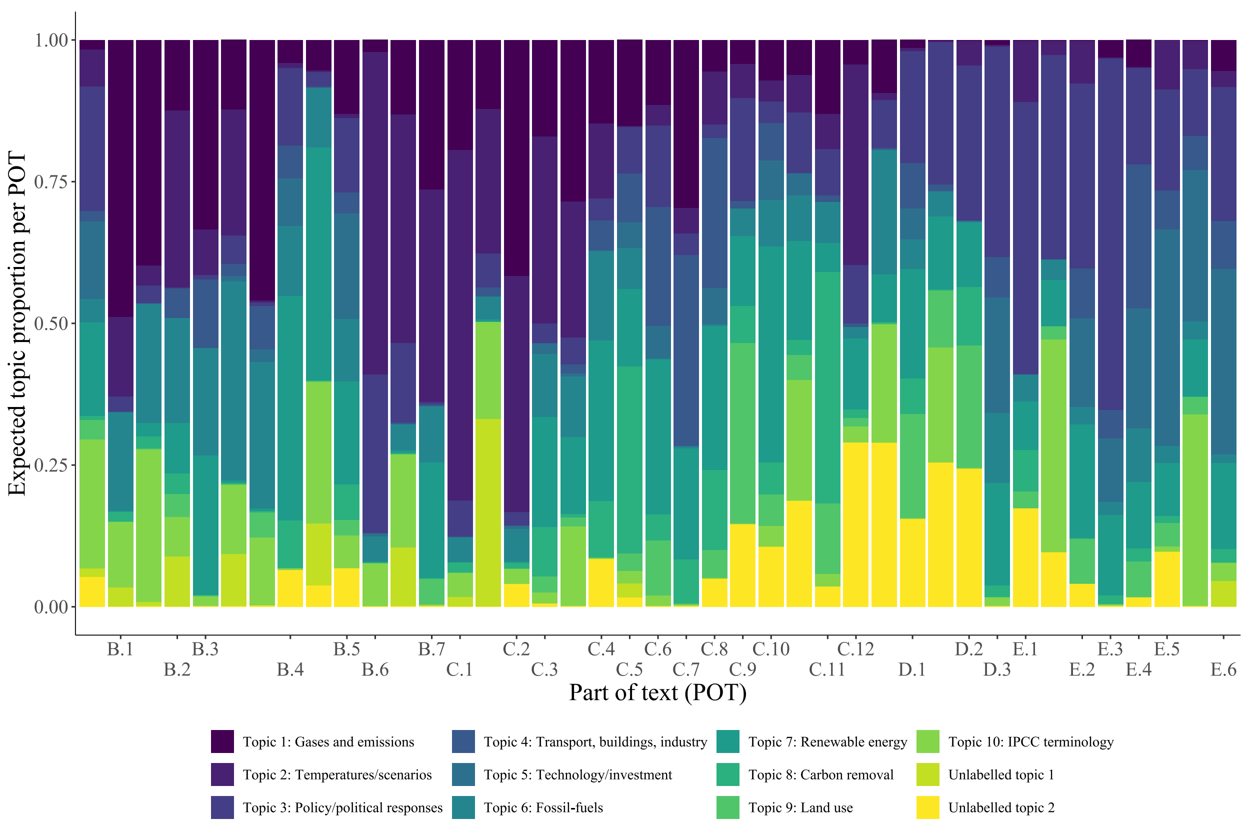

FIGURE B.3: Proportion of predicted topics per POT as estimated from keyATM model.

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 $\times$ 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 $\times$ 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 $\times$ 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 $\times$ 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 $\times$ 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 $\times$ 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.

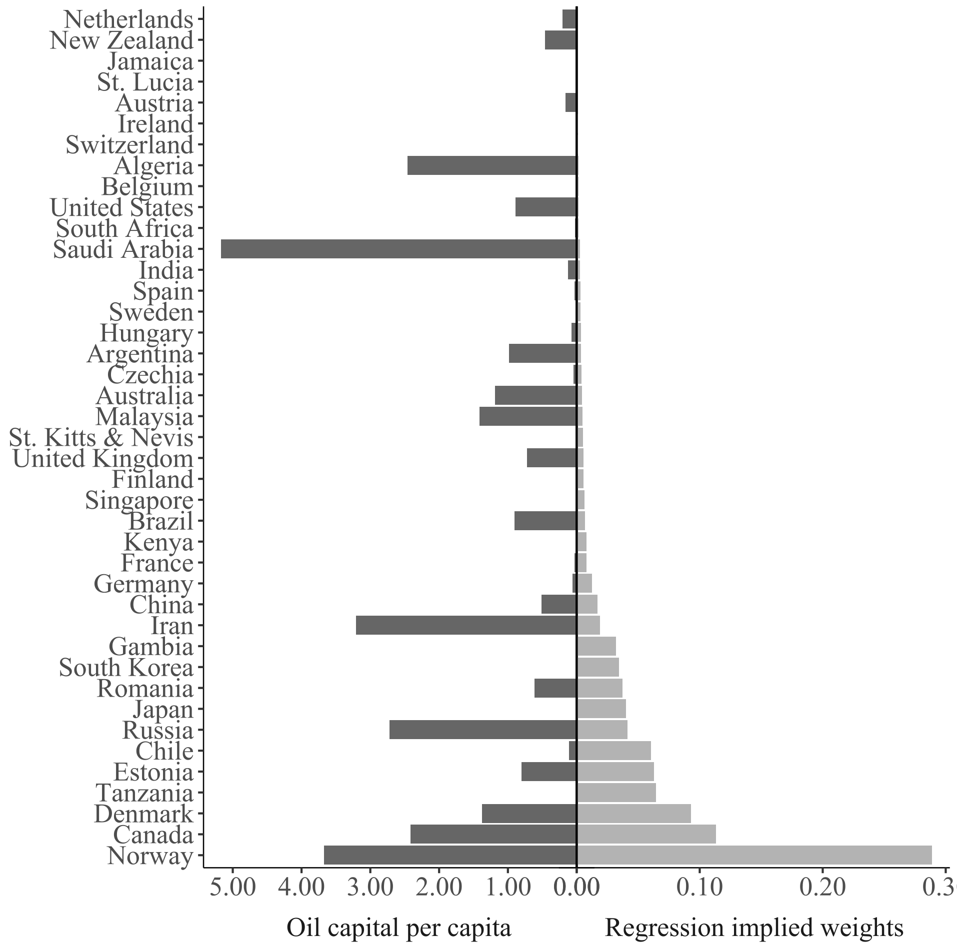

FIGURE B.4: Regression implied weights: oil capital per capita.

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.

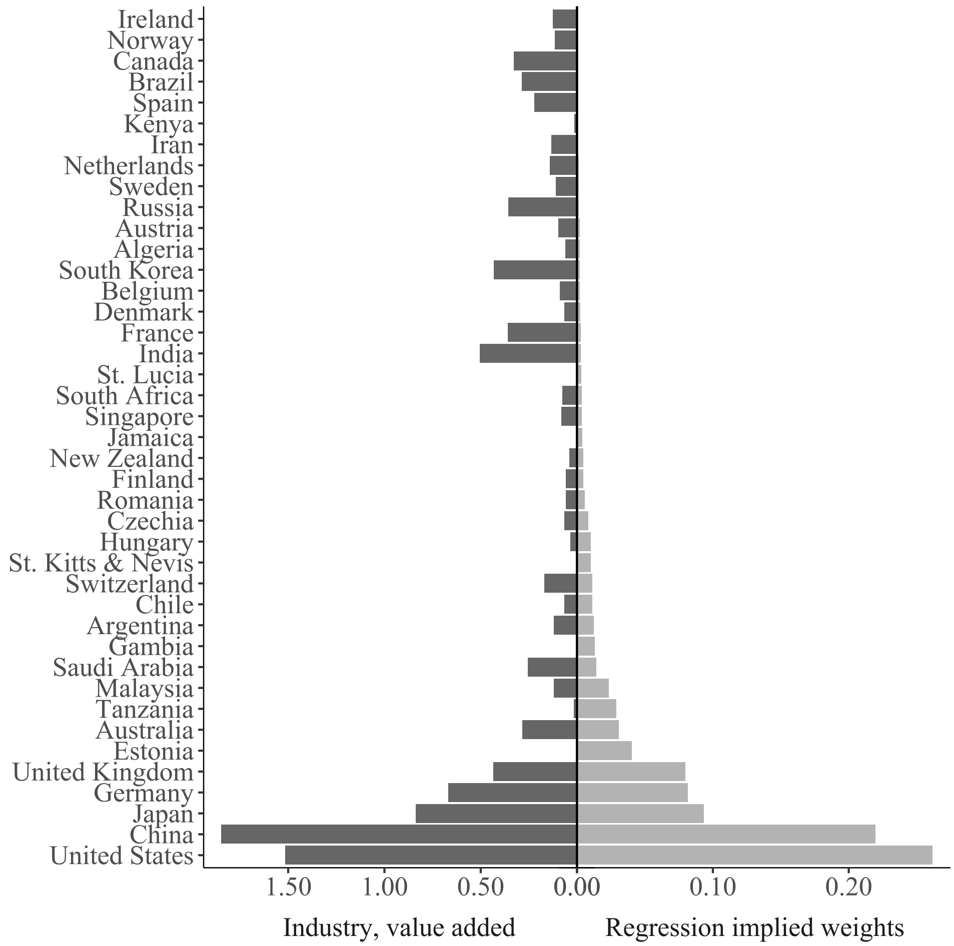

FIGURE B.5: Regression implied weights: industry value added.

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.

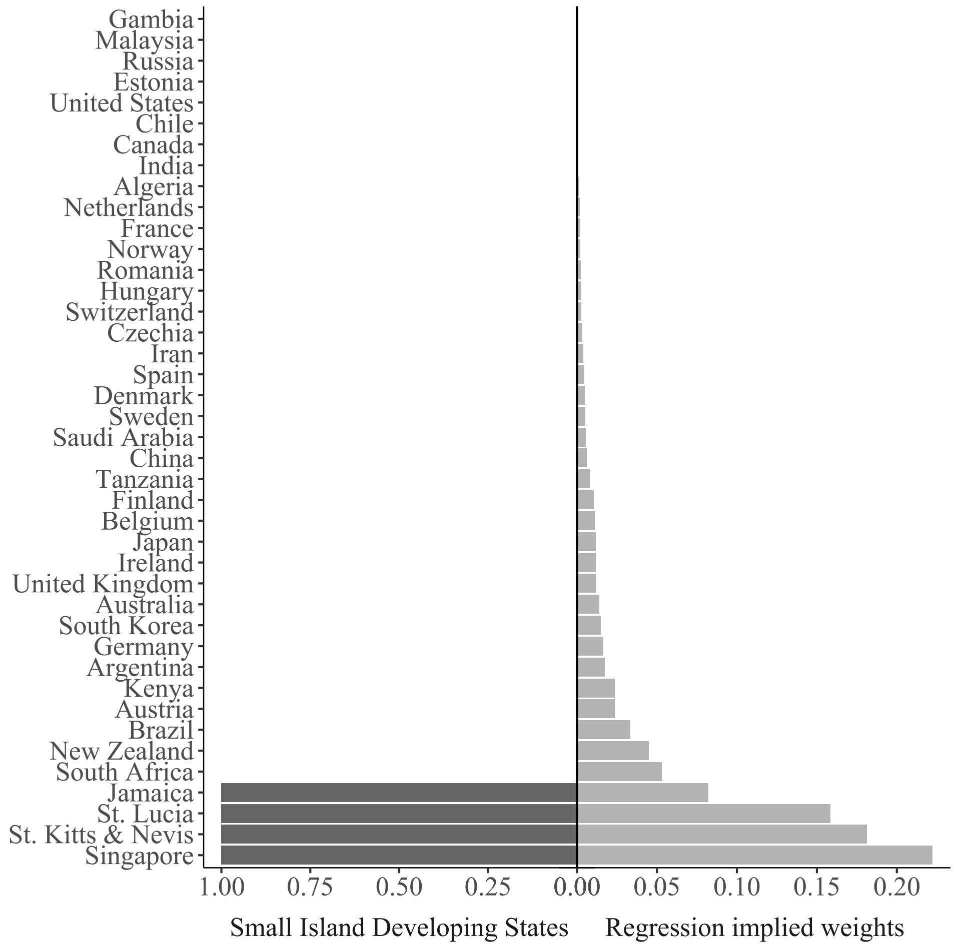

FIGURE B.6: Regression implied weights: SIDS membership.

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.

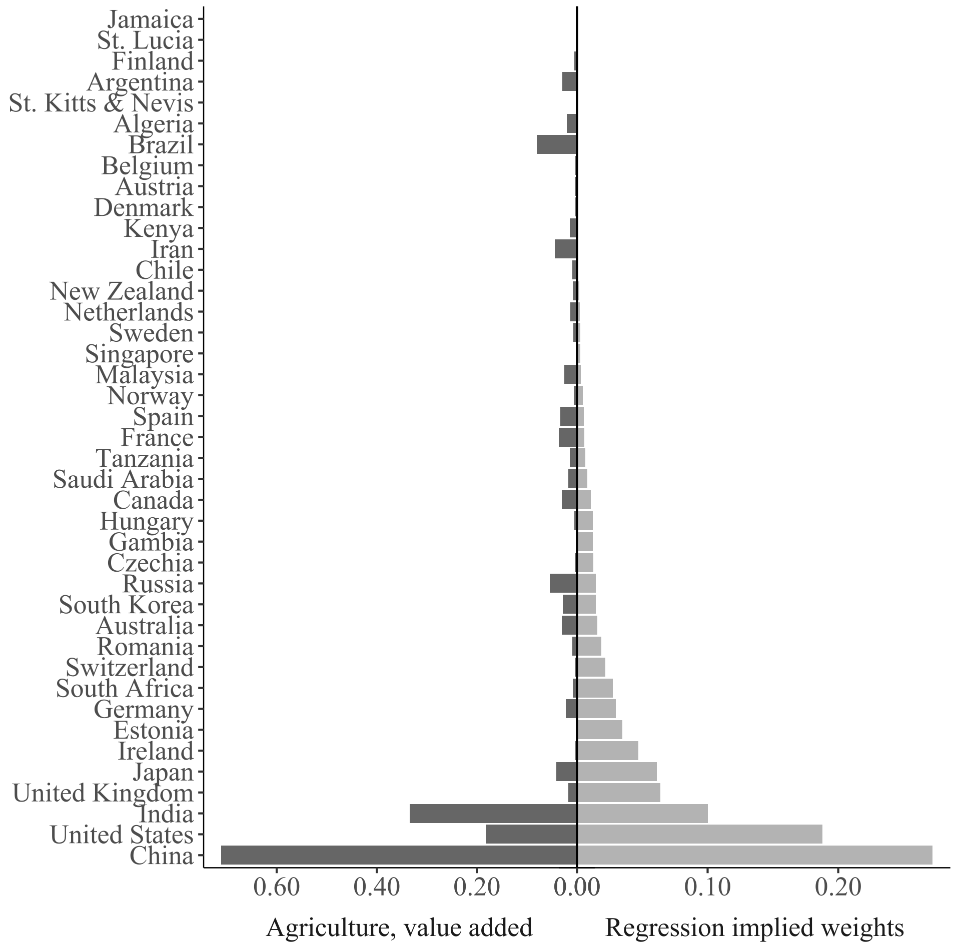

FIGURE B.7: Regression implied weights: agriculture value added.

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.

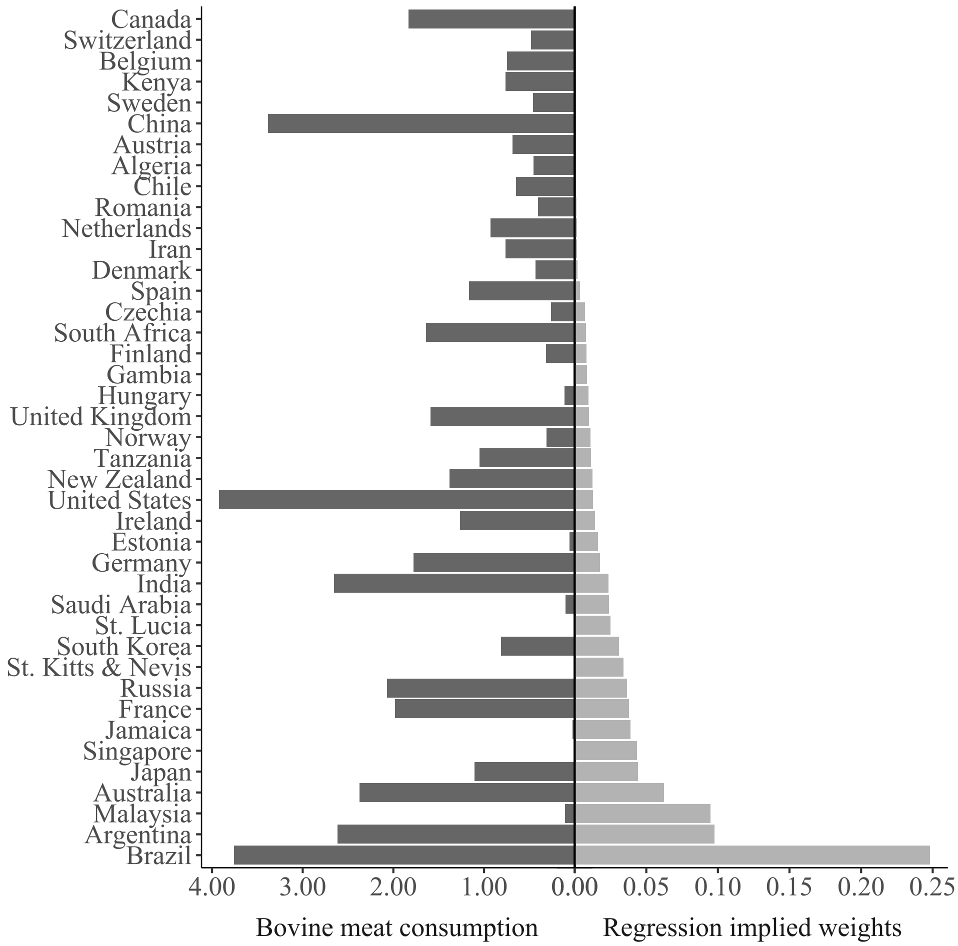

FIGURE B.8: Regression implied weights: economic value of bovine meat consumption.