Do Literature Syntheses Boost Academic Visibility? Causal Evidence from IPCC Author Turnover

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Abstract

Of the 15,130 papers cited in the IPCC's flagship mitigation assessment (AR6, 2022), only 55 appeared in economics' Top 5 journals, yet being cited by the IPCC causally increases a paper's annual citations by 67%. This paper provides the first causal estimates of how science-policy syntheses reshape citation trajectories across an entire field, using the IPCC Working Group III reports as a laboratory. Because citation stocks determine career outcomes and shape future research investment, understanding what drives citation reallocation across an entire field, and who benefits from it, is a first-order question for the economics of science and for the design of science-policy institutions.

I construct a panel of 33,247 papers cited in AR5 (2014), SR15 (2018), and AR6 (2022) matched to 80,000 journal-year controls, with annual citations tracked through 2024. An event-study difference-in-differences design shows AR6 inclusion yields roughly 2–4 additional citations per year. To address residual endogeneity, I exploit the 77% turnover in IPCC chapter authors between AR5 and AR6 as an instrument. Incoming authors bring their own prior bibliographies: a paper frequently cited by newly appointed AR6 authors before their appointment gains a quasi-randomly higher probability of IPCC inclusion, independently of its intrinsic quality or citation trajectory. The resulting 2SLS estimate implies a 67% increase in annual citations (7 additional citations per year off a median baseline of 11). A null result for SR15 serves as a falsification test. The citation premium is heterogeneous: strongest for interdisciplinary journals and mixed Global North–South author teams, while papers by exclusively Global South researchers receive no statistically significant boost. At the field level, IPCC endorsement reallocates rather than expands scholarly attention: endorsed papers gain citations at the expense of non-cited work on the same topics, with a 10-percentage-point increase in a topic's IPCC coverage associated with 1.6 fewer citations per year for uncited papers in that topic, and no detectable change in total topic-level citations. This reallocation disproportionately benefits higher-quality work, suggesting the IPCC performs its curatorial role effectively. Recognising IPCC inclusion in tenure and promotion systems would better align academic incentives with societal impact.

1 Introduction

Scientific attention is scarce, and citations function as a primary currency of recognition within academia. Institutions that assess and synthesise knowledge may therefore act as allocators of visibility, shaping which research receives sustained attention. The Intergovernmental Panel on Climate Change (IPCC) represents one of the most influential such institutions. Yet its citation patterns reveal a striking disconnect: of the 15,130 references cited in the mitigation volume of AR6, only 55 appeared in economics' Top-5 journals.

This raises two questions. Does endorsement by such an institution causally shift citation trajectories? And does it expand total attention or merely reallocate recognition across studies?

This paper This paper asks whether endorsement by a flagship science-policy institution causally reshapes academic recognition and at whose expense. Identifying this effect is difficult because IPCC-cited papers are not randomly selected: simple comparisons confound endorsement with underlying quality. I first implement an event-study difference-in-differences design comparing cited papers to journal-year matched controls. I then exploit the 77% turnover in IPCC chapter authors between AR5 and AR6 as an instrument for inclusion. Author appointments are governed by procedural rules ensuring renewal and balance across gender, regions, and disciplines. Incoming authors bring distinct prior bibliographies, so a paper frequently cited by newly appointed authors gains a quasi-randomly higher probability of inclusion, independently of its quality or trajectory. I use the share of incoming authors who had cited a paper before 2018 as an instrument for its AR6 inclusion.

I examine three patterns of endorsement effects. I first show that the citation premium is heterogeneous across disciplines and regions, with Global North researchers capturing disproportionate gains. I then rule out mechanical self-citation as the driver, showing that post-AR6 gains originate from the broader research community, explicitly accounting for self-citation and chapter-level author overlap. Finally, I demonstrate that endorsement reallocates rather than expands attention, crowding out uncited substitutes within narrowly defined topics.

Context Every six to eight years the IPCC distils tens of thousands of studies into a single assessment that guides international negotiations, investment flows, and domestic regulation. The IPCC reports have been cited as the primary source for the historical decision of the International Court of Justice recognising that "the human right to a clean, healthy and sustainable environment is essential for the enjoyment of other human rights" (ICJ, 2025).[1]

Relevance Flagship scientific assessments—of which the IPCC remains the gold standard—are playing an increasingly central role in the policy landscape. This rise reflects two trends: first, the overwhelming volume of academic publications has created demand for more selective, authoritative forms of endorsement beyond peer review; second, policymakers are seeking clearer, evidence-based guidance on complex issues, with visible links between science and policy outcomes. Beyond the Summary for Policymakers, the bulk of the report is mostly read by scientists themselves, the IPCC synthesises the literature and thus establishes boundaries of relevance, and signals recognition to the studies it cites. In economics, this creates a tension: academic incentives favour methodological innovation and elite journal publication, while the

[1] Paragraph 74, p35, "The Court will consider these issues in more detail. In so doing, it will rely primarily on the IPCC reports, which participants agree constitute the best available science on the causes, nature and consequences of climate change. ", and further paragraphs 75 to 87 discussing IPCC findings as context to the ruling.

IPCC prioritises clarity, interdisciplinarity, and policy relevance. Thus, IPCC inclusion offers an alternative path to career visibility, especially for impactful work that top journals may overlook.

Despite its limitations, the IPCC has become the model for science-policy synthesis. The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) was created in 2012, and has published a common report with the IPCC in 2021. In June 2024, the Intergovernmental Science-Policy Panel on Chemicals, Waste and Pollution (ISPCWP) was created to provide scientific advice on these "under-supported pillars of the global environmental agenda"**?**. These three organisations operate under a mandate of the United Nations (UN) and their agencies and are intergovernmental, and are as such governed by member states. This model has also extended beyond the UN system. For instance, in the field of artificial intelligence, France and Canada announced the creation of The International Panel on Artificial Intelligence **?**. In the same trend, an international panel of experts was tasked with producing science-based assessments of AI risks at Bletchley Park AI Summit (International AI Safety Report, **?**). In August 2025, the United Nations General Assembly established the Independent International Scientific Panel on Artificial Intelligence **?**.

Method I construct a comprehensive panel of 33 247 economics papers cited across AR5 (2014) and AR6 (2022) plus three Special Reports, matched to 80 000 control articles from the same journals and publication years. Annual citation counts (2000–2024) are merged from OpenAlex and Scopus, while author affiliations classify papers into Global-North, Global-South, and mixed teams.

The analysis proceeds in two layers. Event-study difference-in-differences estimates the average citation trajectory of cited versus uncited papers, conditioning on age, journal fixed effects, and pre-trend quality.

Identification strategy I exploit the quasi-random turnover of IPCC chapter authors between AR5 (2014) and AR6 (2022) as an instrument for a paper's inclusion in AR6. About 77% of the author team was replaced between reports — a renewal rate driven by the IPCC Bureau's procedural mandate to achieve geographic, gender, and disciplinary balance through open self-nomination and country-focal-point appointment. This reshuffling underpins the paper's identification strategy and parallels judge reassignment or referee rotation in empirical designs (Galasso and Schankerman, 2015; Kling, 2006). Crucially, author appointments were finalized in January 2018, making the composition of the incoming cohort predetermined relative to any post-2018 citation shocks.

The instrument For each paper i, I construct the fraction of newly appointed AR6 authors who had previously cited paper i before 2018. Incoming authors bring their own prior bibliographies, so a paper cited by many new arrivals has a higher probability of appearing in AR6 — not because of any intrinsic change in its quality or trajectory, but because of the quasi-random draw of who joined the team. I restrict the sample to papers published before 2018 to ensure all pre-treatment characteristics are fixed before the instrument is realized.

IV validity The instrument satisfies the four standard conditions. *Relevance*: the first-stage F-statistic exceeds 200 across all specifications, far above conventional weak-instrument thresholds. *Exogeneity*: author appointments follow procedural quota rules unrelated to individual paper trajectories; I additionally control for pre-appointment citation stock and journal × publication-year fixed effects to absorb any residual confounding through baseline quality or prestige. *Exclusion*: author turnover can only affect post-2022 citations through the channel of formal IPCC inclusion — incoming authors' prior citation habits do not directly shape the research community's subsequent reading decisions. *Monotonicity*: a higher share of incoming "citers" weakly increases, and cannot decrease, the probability of inclusion.

I examine the the tendency of IPCC authors to self-cite and the impact on citation numbers by leveraging the chapter-level author turnover. I further investigate where are the citations received by IPCC reference coming from: IPCC authors, reviewers or outsiders, and whether these outsiders are more from global South or Global North countries, thus quantifying the local endorsement impact of the IPCC.

I finally conclude by studying the additionnality of IPCC induced citations. I study the spillover impacts of IPCC on topic-adjacent papers never cited in the IPCC, and study which papers benefits from the IPCC in terms of quality, thus providing a welfare assessment of such a review exercice.

Results This paper yields three main findings.

First, being cited in the IPCC leads to a clear citation premium. Comparing referenced papers to a matched control group, I find that inclusion in AR6 is associated with an average increase of two citations per year, controlling for observable characteristics. This effect begins to materialize roughly two years before the official publication date in 2022, consistent with the early circulation of draft reports. Parallel pre-trends are verified. A similar pattern holds for AR5, with an even larger and more persistent effect: cited papers gained about four additional citations per year, with the boost still visible a decade later.
To strengthen causal identification, I exploit author turnover between AR5 and AR6. Using the replacement of IPCC authors—who cited different work prior to their appointment—as a source of exogenous variation, I estimate that inclusion in the IPCC increases citations by approximately 67%, or about 7 additional citations per year, relative to a median baseline of 11.

Second, to validate, strengthen, and disaggregate the results, I examine both the characteristics of cited papers and the provenance of the citations they receive.
The citation premium is heterogenous. It is significantly stronger for non-economics journals, and largest for papers co-authored by researchers from both the Global North and South, suggesting that international and interdisciplinary collaboration increases visibility. However, papers authored solely by Global South researchers do not experience a citation boost, in contrast to those by Global North authors, pointing to persistent disparities in recognition even within inclusive scientific processes.
I show that the citation boost for IPCC-cited papers is not driven primarily by IPCC-affiliated authors, indicating that the endorsement effect extends beyond a small inner circle. In fact, papers never cited by the IPCC receive an even larger share of their citations from IPCC-related authors—reflecting those authors' high publication and citation activity in the field, rather than any preferential reinforcement. The observed citation boost comes mainly from the broader

research community, particularly from the Global North. While Global South authors contribute a larger share of citations over time, the boost in citation due to the IPCC report publication is only driven by Global North scholars.
A significant numbers of references, about 20% have a least one AR6 authors (various role) in their team. However,the distribution of references which one authors is involved in the IPCC is not random, 13% are cited in a chapter where one of their author is also involved. I use the chapter-level turnover of authors between AR5 and AR6 to show that there is significant self-citations, and not just an overlap between relevant scientists involved in the IPCC and in the field. Authors still cite a significant number of papers by the previous team, even if they're not involved in the process anymore, but the observed level of self–citation in AR6 significantly exceeds what would be expected had the AR6 author team been identical to that of AR5.

Third, I use within-topic panels to examine how IPCC endorsement affects both cited papers and uncited substitutes on the same topic. The citation boost is largest when the IPCC cites only one or two papers on a given subject, reinforcing the idea that IPCC acts as a focal point, concentrating attention on a single "reference" paper. In contrast, when a topic is broadly covered, the citation boost is diluted across many papers. Papers never cited by the IPCC but working on heavily covered topics see slower citation growth than those in less-covered areas, suggesting a substitution effect. A dose–response analysis confirms this pattern: a 10% increase in the share of a topic's papers cited by the IPCC is associated with a decrease of 1.6 citations per year for uncited papers in that topic.
I find no evidence of any change in the total number of citations at the topic level, indicating that the IPCC process is a pure reallocation of attention and citations. This reallocation disproportionately benefits high-quality work: the gains are concentrated among papers in the top 20% of citations within their cohort before AR6. In that sense, the IPCC appears to perform its curatorial role effectively, endorsing high quality work. However, the process also reinforces existing inequalities in visibility and geographic bias in citation behaviour, thus raising questions about using citation counts as a proxy for quality.

Contributions This paper makes three principal contributions to the literatures on (i) the economics of science and bibliometric methods, (ii) climate–policy assessments and the IPCC, and (iii) equity, diversity, and global participation in climate research.

First, this paper offers the first causal estimate of how flagship science–policy syntheses, of which IPCC is the gold-standard, reshape the citation trajectories of both cited and uncited work across an entire field. By leveraging quasi-random author turnover, akin to judge reassignment designs in economics (Galasso and Schankerman, 2015; Kling, 2006), I treat changes in reference-list composition as an exogenous shock and quantify its ripple effects on journals, topics, and individual papers. While prior causal studies of citation dynamics have focused on dramatic shocks like the premature death of star scientists (Azoulay et al., 2010, 2019), this paper introduces a novel instrument grounded in the internal governance of synthesis reports. It also bridges literatures on the evolving topography of economics research (Angrist et al., 2017; Wei, 2019; Garg and Fetzer, 2025), the cross-fertilization and interdisciplinarity of economic work (Fourcade et al., 2015; Angrist et al., 2020; Card and DellaVigna, 2013) , and critical reflections on bibliometric bias (Hamermesh, 2018; Jensen et al., 2008; Rousseau and Rousseau, 2021). I document a persistent disconnect between academic prestige—as proxied by publication in Top-5 economics journals—and policy relevance, as proxied by IPCC inclusion (Heckman and Moktan, 2020; Osterloh and Frey, 2020). More broadly, by quantifying how an IPCC-style review body reallocates attention within climate mitigation research, this paper contributes to the emerging "science of science" agenda (Fortunato et al., 2018) and to debates on the welfare consequences of academic research and citation as a recognition mechanism (Bornmann, 2013; Bornmann and Marx, 2014; Ugur et al., 2020; Fieldhouse and Mertens, 2025; Dyevre, 2023; Rousseau et al., 2021).

Second, this paper speaks directly to the literature on climate-change literature and schorlarship, and the research focusing on the role and process of the IPCC in particular. Prior work has documented the rapid expansion and topical topography of climate-change research, highlighting the lack of social-science contributions to technical mitigation debates (Callaghan et al., 2020; Grieneisen and Zhang, 2011; Minx et al., 2017; Haunschild et al., 2016). Early scientometric analyses focused on AR3 references (Bjurström and Polk, 2011; Vasileiadou et al., 2011). Analysis of the downstream impacts of IPCC reports on scientific output throught he citation of the report itself (Vasileiadou et al., 2011) and the impact on climate activism (Doran et al., 2023). Others have critiqued the IPCC's narrowing influence—its sidelining of certain disciplinary, regional, and indigenous perspectives—and documented persistent North–South and gender imbalances among WGIII authors (Hughes and Paterson, 2017; Hughes and Vadrot, 2019; Pollitt et al., 2024; Corbera et al., 2016). Manu biases in IPCC processes have been documented and initated calls and proposals for reform including broader collaboration with the public (Hermansen et al., 2023; Carraro et al., 2015; Asayama et al., 2023; De-Gol et al., 2023). Meanwhile, economists' contributions to mitigation assessments remain limited, despite calls for deeper engagement of economic analysis (Noy, 2023; Henry, 2025; El Tinay and Schor, 2025). Building on studies of policy-document citations in Overton (Bornmann et al., 2022), we move beyond descriptive mapping to provide the first causal quantification of how IPCC citation decisions reallocate scholarly attention—benefiting both referenced and unreferenced work—across journals, topics, and regions.

Third, this paper contributes to debates on diversity and inclusion in climate-change scholarship by tracing how IPCC endorsement interacts with existing geographic, disciplinary, and gender imbalances. Climate change mitigation literature is still very siloed between disciplines (O'Neill et al., 2010; Callaghan et al., 2020; Grieneisen and Zhang, 2011) that marginalise social-science perspectives in technical mitigation debates. Baninla et al. (2022) document the under-representation of African researchers and Africa-focused studies in the mitigation literature. More globally, there is a persistent geographic gaps in economic research (Aigner et al., 2025) and specifically within development studies central to WGIII (Amarante et al., 2022). Even as IPCC author diversity has modestly improved over time in terms of Global-South representation and gender balance, inequalities remain (Tandon, 2023). Especially, gender disparities endure at multiple levels: among IPCC authors (Gay-Antaki and Liverman, 2018), in top economics journals (Koffi, 2021), and across the broader economics profession (Berland et al., 2023). The lack of gender disaggregation is one of the limitations of this paper. Indigenous knowledge remains largely excluded from syntheses like IPBES, underscoring a wider pattern of marginalization (Hughes and Vadrot, 2019). By disaggregating the citation premium from IPCC inclusion across author regions and team compositions, I show that mixed Global-North/South collaborations secure the greatest visibility gains, furthering the results of (Corbera et al., 2016).

Implications for Economists These findings have direct implications for how economics departments evaluate climate researchers. IPCC inclusion represents a credible, externally validated signal of policy relevance that current tenure systems largely ignore in favour of journal rank. My estimates imply that a single AR6 citation generates roughly 7 additional citations per year — a visibility gain comparable to publication in a well-regarded field journal. Recognising IPCC contributions in promotion decisions, alongside journal publications, would better align individual incentives with the profession's stated commitment to policy impact. A natural next step to be added before the ESEM conference is linking IPCC-driven recognition directly to career outcomes: tenure decisions and grant awards. It would quantify how much the current misalignment actually costs researchers who prioritise policy-relevant work.

Plan The remainder of this article is structured as follows. Section 2 outlines the data sources and empirical methods, and the journal cited by the IPCC. Section 3 examines the IPCC's role as an endorsement mechanism, estimating the citation premium using an average treatment effect on the treated (ATT) framework. In Section 4, I exploit author turnover as an exogenous source of variation to identify causal effects using an instrumental variables approach (LATE). Section 5 investigates self-citation dynamics, and Section 6 analyses the geographic and institutional provenance of citations. Section 7 evaluates whether IPCC inclusion reallocates or expands overall scholarly attention and overall welfare implications. Section 8 concludes.

2 Methods & Data

My goal is simple: recover every reference cited in three recent IPCC volumes (AR6 WG III 2022, AR5 WG III 2014, and the 2018 1.5°C Special Report), match those references to external bibliometric databases, and compare their citation trajectories with a discipline–year–journal–matched control group. Full replication code and raw outputs are archived online.

Reference extraction. Each chapter ends with a two-column bibliography. A four-step parser—*(i) PDF-to-text*, *(ii) chapter boundary detection*, *(iii) reference-page flagging*, *(iv) line-reassembly*—isolates individual citations. A reference is recognised when an author block is followed by a four-digit year and a colon or a change in indentation. Appendix A provides details on the exact process. The same routine (with minor tweaks for punctuation quirks in AR5) yields 17,526 references, covering 15,130 articles, chapters, books or documents (Table 1).

Table 1: References in IPCC reports

	AR6	AR5	SR15
Reference instances	17,526	11,937	3,231
Unique references	15,130	8,779	2,774

Journal matching. To address inconsistencies in journal naming across IPCC reference lists—ranging from irregular capitalisation and abbreviations to punctuation errors introduced by PDF formatting—I implemented a multi-step journal name normalisation procedure. Starting from raw strings, I applied systematic cleaning (e.g., trimming whitespace, removing punctuation, resolving abbreviations) and matched entries against two external abbreviation databases: Web of Science and the University of British Columbia's journal abbreviation list. For unmatched entries, I used OpenAlex metadata to retrieve journal names via DOI lookups, correcting common DOI parsing errors when necessary. This process, iterated over twenty-five rounds, successfully reconciled most variants to canonical journal titles. Fuzzy matching was tested but ultimately set aside due to high computational cost and limited marginal return.

Journal classification. To tag outlets as Economics or Non-economics and to assign a quality tier, I combine four lists. First, the CNRS Section 37 ranking (2020) places economics journals into categories 1–4; second, the 2022 LSE departmental lists rank journals used in tenure decisions across Economics, Geography and related fields; third, the 2024 SCImago Journal Rank (SJR) supplies citation-weighted percentiles, which I collapse to quartiles (Q1–Q4); and, finally, the June 2025 RePEc roster provides the broadest catalogue of economics-relevant titles, extending to multidisciplinary venues such as Science, Nature, Nature Climate Change and PNAS. A journal is flagged "Economics" if it appears in either the CNRS list or RePEc.

Metadata and citations. I query two APIs: *OpenAlex* (open, DOI–centred, citation years 2012–2024) and *Scopus* (Elsevier, longer backfile). Requests are throttled to 5 per second. The matching logic is

1. If the PDF already prints a DOI, fetch metadata directly.
2. If the DOI fails or is missing, search OpenAlex by {journal, title, year} with progressively relaxed keys; accept the top hit if the Levenshtein similarity score of the titles is superior to 0.80.
3. Remaining edge cases are resolved manually.

Citation source selection. For every parsed reference of AR6 and SR15 I use OpenAlex (because it is open-source, rate-limited only at generous thresholds) to fetch the yearly citation counts since publication and until 2024. OpenAlex provides usable annual citation counts only from 2012 onwards, consequently for AR5 (2014) I relied on the Scopus "Citation Count Overview" API, which supplies longer historical series. Next step is to fetch the citation count for AR6 using Scopus to check the OpenAlex number, and see whether I get the same results I obtain citation histories for 11,355 unique references in AR6; 4,344 in AR5; and 2,774 in SR15.

Author linkage. To link cited works to IPCC contributors, I recover full author lists for each reference and match them to the chapter-level authors printed in the reports. Where references include "et al.", I supplement the missing names using OpenAlex; otherwise, I parse and clean the full author string directly from the PDF, correcting for formatting inconsistencies such as reordered initials or broken hyphenation. Each chapter's contributor list is scraped from introductory pages and provides a set of fully spelled-out names. I harmonise the two datasets using two name-matching keys (surname plus first initial; surname plus all initials) to account for inconsistent name formats across sources. This process yields a comprehensive author–reference mapping: 115,613 instances in AR6 and 38,448 in AR5, which I use to identify which cited papers were authored by report contributors.

Control papers. To assess whether IPCC-cited papers exhibit distinct citation patterns, I construct a control group of non-cited papers matched by journal and publication year. Each journal–year cell defines a sampling stratum, ensuring that control papers share similar exposure to outlet prestige and vintage effects. I do not attempt to match on field for multidisciplinary journals such as Science, Nature, or PNAS, instead controlling for citation dynamics through journal fixed effects and citation history in regression specifications. Within each cell, I exclude treated articles and draw a random sample up to ten times the number of IPCC references, constrained by the number of available papers. Citation histories for these control papers are retrieved from the same databases as the treated group—OpenAlex for AR6 and SR15, Scopus for AR5. This process yields 70,332 matched controls for AR6, 32,663 for AR5, and 15,229 for SR15, forming a balanced comparison set aligned on outlet and timing.

Limitations. I note potential biases due to database coverage (e.g., Scopus vs OpenAlex) and limitations of automated reference parsing (possible mis-parsing in some chapters). API rate limits and licence restrictions may affect completeness. Manual checks were performed for ambiguous cases, but residual errors may persist.

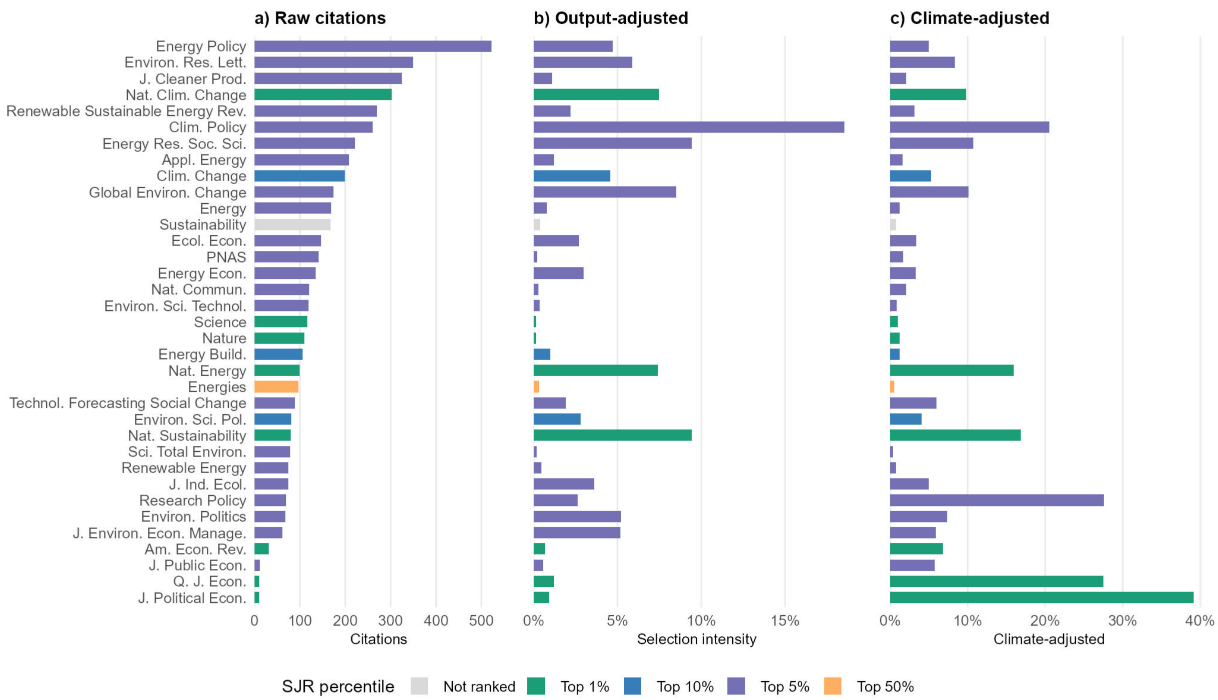
Descriptive analysis of WG III references I have identified 15,130 unique references in the IPCC AR6 WGIII report. I can identify a journal for 10,868 of them, spanning 986 different journals.

Figure 1 shows the twenty-five journals most frequently cited in the IPCC AR6 WG III bibliography, both in absolute terms (left panel) and normalized by each journal's average annual article output (right panel). In absolute counts, *Energy Policy* leads with over 500 unique IPCC citations, followed by *Environmental Research Letters*, the *Journal of Cleaner Production* and *Nature Climate Change*.

Adjusting for annual output, *Climate Policy* emerges as the clear front-runner: although it publishes only a few dozen papers per year, nearly one in three is cited by WG III. Similarly, *Nature Climate Change* ,*Nature Energy* and *Nature Sustainability* are relatively more cited than other journals, reflecting the IPCC's appetite for high-impact high-level studies on energy transitions. Conversely, broad-scope journals such as *Science* and *Nature* show a marked dilution effect. Indeed, despite their overall visibility, only a small fraction of their output addresses mitigation-relevant topics (see Figure 18 in Appendix F.1 for the share of papers dedicated to each climate change in each journal). About 12-15% of their articles are related to climate change, correcting their annual output for this proportion does not place them among the most cited journals. Among field journals, *Journal of Cleaner Production*, *Sustainability* and *Energies* see a substantial drop when normalized, indicating that the high number of papers cited from these venues is actually a small share of their publication volume, and that most articles are climate change related, thus citable by the IPCC. Established outlets focused on economics and policy — *Ecological Economics*, *Energy Economics* and *Applied Energy* — maintain solid normalized citation rates, underlining the importance of top-field publications.

The diversity of journals in the IPCC top 25 cited journals illustrate the interdisciplinary of the IPCC. Beyond the diversity of disciplinary journals, interdisciplinary journals and papers that bridge economics, engineering and social science appear disproportionately in WG III, highlighting the value of cross-sectoral approaches. It hints at relevance rather than journal prestige when citing papers with diversity in journal overall quality as measured by the SCImago Journal Rank (SJR) (colour legend). Most journals – but not all, notably *Sustainability* (MDPI) which published about 17,000 papers in 2022 – are within the top 10% of journals. Journals whose scope closely matches the IPCC's mitigation mandate—regardless of impact factor or reputations—are as likely to be cited as other more prestigious journals.

Figure 1: IPCC references per journal in absolute and relative to their annual output



Note: *Top 25 Journals cited in the IPCC AR6 WGIII report in absolute numbers (left panel), and relative to the average annual output of each journal (right panel). and the 4 remaining so-called top 5 journals. Colours indicates the quality of the journal, measured by the SCImago Journal Rank (SJR).*

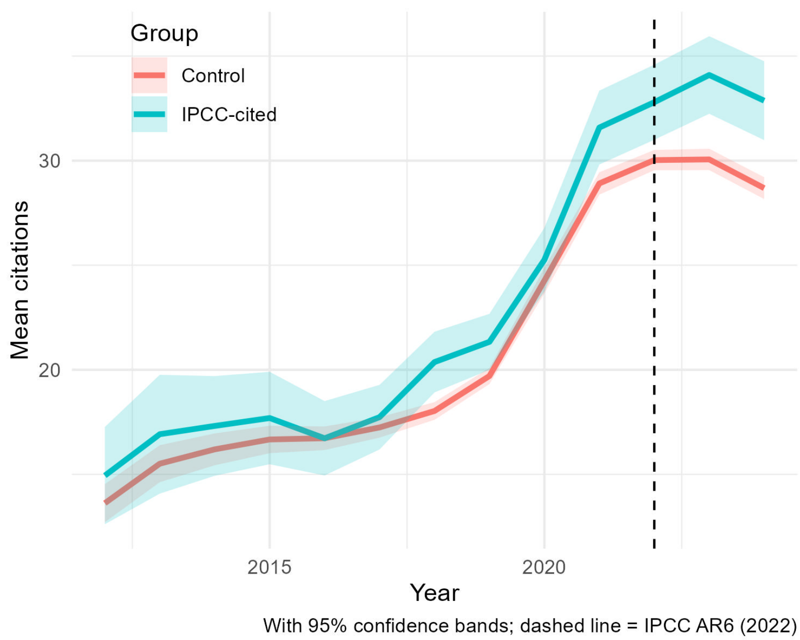
If IPCC inclusion is indicative of the quality and relevance of papers, it gives advice for young research eager for visibility. Articles that answer the IPCC's policy-relevant questions-often highly technical - are more likely to be cited, even if in specialised venues. In other words, for IPCC citations, fit beats fame. Papers bridging economics, engineering and social science get disproportionate visibility inside WG III. Inter-disciplinarity matters for producing relevance pieces. Broad-audience pieces (Nature Energy, Science) complement, and do not substitute for, rigorous studies in field-specific journals with a more technical focus and maybe niche methods.

3 Citations impact

The central question of this paper is whether being cited in an IPCC report acts as a form of endorsement, elevating the visibility and influence of the referenced work.To investigate this, I apply causal inference methods to compare the citation trajectories of papers included in the IPCC with a matched control group of similar, but uncited, papers. I further leverage the exogenous turnover of authors between AR5 and AR6 to create a exogenous shock to potential gatekeeping. Put simply, and more trivially, this section asks: is being cited in the IPCC good news for a paper, and how much does it matter?

Description of the sample Figure 2 plots the unconditional mean yearly citation trajectory for papers subsequently cited by the IPCC ("treated") and for a matched control set.[2] A pronounced divergence emerges in 2020: while both series trend upward, the slope for IPCC-cited papers steepens markedly, foreshadowing the formal publication of the Sixth Assessment Report (AR6) in 2022.

Figure 2: Average yearly citations: AR6 references vs. control papers



Notes: Shaded bands show 95% confidence intervals. Vertical dashed line marks the release of AR6 (2022).

3.1 Empirical strategy

To quantify the causal effect of being cited in an IPCC report, I estimate a standard difference-in-differences specification using a two-way fixed effects (TWFE) model (Angrist and Pischke, 2009).

[2]The control sample is selected on *ex ante* observables : journal, year of publication, so as to mirror the treated group. See Appendix A for details.

Specifically, I regress the number of citations received by article i, published in journal j, in year t, on a post-treatment indicator, a treatment indicator, and their interaction:

$$\mathrm{cit}_{ijt} = \beta\,(\mathrm{Post}_t \times \mathrm{Treat}_i) + \alpha\,\mathrm{Post}_t + \gamma\,\mathrm{Treat}_i + \delta\,\mathrm{Cit3}_i + \mu_{ijt} + \varepsilon_{ijt}, \tag{1}$$

where cit_{ijt} is the number of citations received in year t; Treat_i is an indicator equal to one if article i was cited in the IPCC AR6 report; and Post_t is an indicator equal to one for years $t \geq 2022$, the publication year of AR6. The term $\mathrm{Cit3}_i$ captures the cumulative citations received by article i in the first three years after publication (before 2020), and serves as a proxy for baseline paper quality and prior visibility. The term μ_{ijt} includes fixed effects for calendar year, publication cohort, and journal. Standard errors ε_{ijt} are clustered at the DOI (article) level throughout the paper. The coefficient of interest is β, which captures the average treatment effect on the treated (ATT), i.e., the change in annual citations post-2022 for articles cited in AR6 relative to comparable uncited articles.

I include a rich set of fixed effects to account for potential sources of confounding variation. Specifically, I control for time since publication to capture the natural citation trajectory of papers as they age, year fixed effects to absorb calendar-year-specific shocks that may influence citation patterns (e.g., global events or field-wide developments), and journal fixed effects to account for persistent differences in citation levels across publication outlets. Additionally, I include publication year fixed effects to control for cohort-specific citation dynamics, and a coarse journal bin classification to capture unobserved heterogeneity across groups of journals with similar scope or prestige.

To assess dynamic effects and test for pre-trends, I estimate an event-study specification that interacts treatment status with a series of event-time indicators relative to the year of IPCC publication:

$$\begin{aligned}\mathrm{cit}_{ijt} = &\sum_{k\neq -1}\Big[\beta_k\,\mathbb{1}\big\{\mathrm{event\_time}=k\big\}_t \times \mathrm{Treat}_i \;+\; \alpha_k\,\mathbb{1}\big\{\mathrm{event\_time}=k\big\}_t \;+\; \gamma_k\,\mathrm{Treat}_i\Big] \\ &+ \delta\,\mathrm{Cit3}_i + \mu_{ijt} + \varepsilon_{ijt},\end{aligned} \tag{2}$$

where event_time indexes the number of years relative to the treatment year (2022), with $k = 0$ corresponding to the treatment year. The coefficients β_k capture the dynamic treatment effects in each event year. This specification allows for visual inspection of citation trends before and after inclusion in the IPCC, and tests the identifying assumption of parallel trends. Fixed effects μ_{ijt} account for article-level heterogeneity and absorbs common shocks over time.

For the AR6, I compare about 7,000 paper in the treated group (IPCC referenced) to 75,000 in the control group (Table 2). For the AR5, I compare 3500 treated doi to 62,000 control papers. I restrict to citations before 2025 (complete year), citations after publication, publication before the IPCC publication (2022 for AR6, 2014 for AR5), and published after 2010 for AR6 and 1997 for AR5 (openalex offers citations from 2012 onwards, I use SCOPUS for the AR5). I restrict to papers being published after 2010 (resp. 1997) as it increases the likelihood of them being included in OpenAlex and as to not bias the estimate with sparse old and likely influential papers. As a result, the number of unique papers in the AR6 sample drops for 10,000 to 7,000.

Characteristics between control and treated group in terms of publication year and journal are comparable. See Tables 19 and 19 in Appendix F.1

Table 2: Dataset characteristics for the AR6 and AR5

	AR6		AR5	
	Observations	Unique doi	Observations	Unique doi
Treatment	51,772	7,011	30,611	3,562
Control	517,152	75,693	469,802	62,277

3.2 Results

3.2.1 AR6 report

Table 3 displays the results of the TWFE estimation of Equation (1).
Cross specifications the point estimates imply that IPCC-cited articles accrue about 2-3 additional citations per annum in the three years following AR6 relative to similar, uncited papers (β on treat×postà). This magnitude is significant, amounting to roughly a 20% increase over the median mean of annual citations (11/year). The result is robust across specifications with various fixed effects. In columns (1) and (3) the variable post is omitted because of collinearity. The higher result in column (5) when the appropriate control for prior quality (Cit3) is not included indicates that the effect is mostly driven by papers with large citation counts, but remains significant. This interpretation is reinforced by the same regressions being performed in log scale[3] for both the yearly citation count (dependant variable) and the accrued citations over the first three years of the papers (Cit3, control). The estimate is slightly negative, about -0.02, meaning a decrease in citations of about 2% (Table 21, in Appendix F). The log scale compressing the distribution of citations, this results is driven by the volume of papers with low citations (skewed citation distribution) and Jensen's inequality.

This combination of results indicates that the endorsement effect of the IPCC matters more for papers already receiving a higher number of citations. Section 7.5 confirms this interpretation by performing a triple-difference analysis on post-treatment indicator, a treatment indicator and a quality indicator.

Event study Figure 3 displays the results of the event study estimation of Equation (2). Post-2020, the treatment effect rises to ≈ 4 citations, plateauing thereafter.

The key result is that the citation effect appears as early as two years before the official AR6 publication date. This early impact is not unexpected: internal circulation of the report begins well in advance, with the Zero Order Draft shared among IPCC authors, followed by the First Order Draft sent to a broad group of expert reviewers. As a result, referenced papers begin to receive increased attention even before the report is formally released.

[3] Precisely $\log(1 + \text{yearly\_citation})$

Table 3: Difference-in-Differences Estimates of AR6 WGIII Report Impact on Yearly Citations

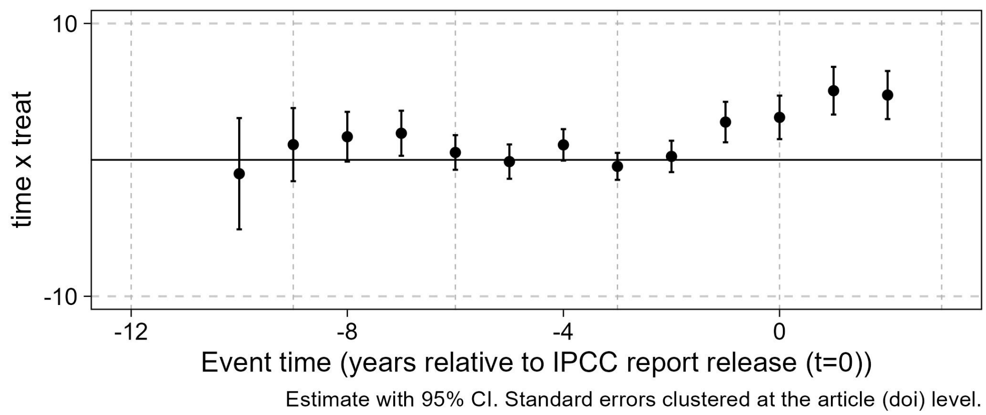
	(1)	(2)	(3)	(4)	(5)
treat	0.3	0.2	0.5	−82.8	2.7***
	(0.4)	(0.4)	(0.4)	(91.0)	(0.8)
cit3	0.3***	0.3***	0.3***	−0.3	
	(0.0)	(0.0)	(0.0)	(0.2)	
treat × post	2.0***	2.0***	1.8**	2.9***	1.8**
	(0.6)	(0.6)	(0.6)	(0.6)	(0.7)
post		0.6	−0.2	−146.4+	−1.0
		(2 426 774.1)	(7 321 459.8)	(85.3)	(8 582 742.2)
Num.Obs.	561 873	561 873	561 873	561 873	568 924
R2	0.563	0.572	0.579	0.775	0.248
R2 Within	0.427	0.435	0.440	0.000	0.000
Std.Errors	by: doi	by: doi	by: doi	by: doi	by: doi
Journal FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Publication Year FE		✓		✓	✓
Time Since Pub FE		✓	✓	✓	✓
DOI FE				✓	

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

Clustered standard errors at the paper (DOI) level.

Each column represents a different fixed effects specification.

Figure 3: Dynamic impact of AR6 citation



Notes: Points denote $\hat{\beta}_k$; bars are 95% confidence intervals. The horizontal line at 0 represents the omitted period $k = -1$.

Pre-treatment coefficients are close to zero and jointly insignificant. I formally test

$$H_0 : \beta_{-10} = \beta_{-9} = \cdots = \beta_{-3} = 0$$

using a Wald statistic with 8 degrees of freedom. The test yields $\chi^2(8) = 12.3$ (p=0.11), I cannot reject the joint nullity of the coefficients and conclude that parallel trends hold, which is the assumption underlying our event-study design.

3.2.2 AR5 report

Figure 4 replicates the analysis for AR5 (trimming the extreme 0.1% outliers). The post-event boost is about the same magnitude (4–6 citations annually). Table 16 in Appendix D replicates the TWFE and confirms the magnitude.

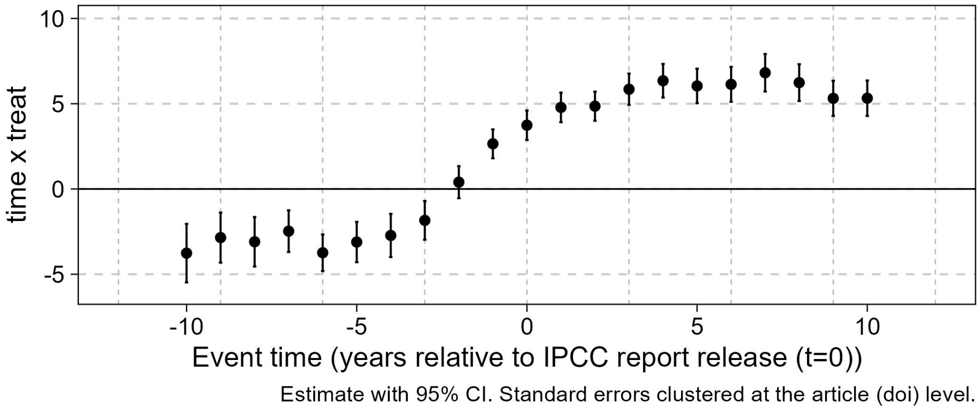
I find the same magnitude despite the citation inflation in climate economics (Haunschild et al., 2016) due to the comparison between carefully balanced panel of treated and control groups, the inflation affecting both.

Three key findings: i) the effect of 4-6 additional yearly citation is constant and only attenuates after roughly eight years, showing a significant and lasting impact of the IPCC. It might create a virtuous cycle, where a more cited paper later attracts even more citations, ii) the effect is significant 2 to 3 years before the official publication of the AR5 report in 2014, which is once again consistent with the WGIII calendar (the window is longer because the publicaiton of the AR6 drafts were pushed back due to the COVID-19 pandemic).

Note that there is parallel trend before 2012 even though the level is negative.

The specification in log scale shows a positive increase relatively to baseline (Table 17 in Appendix D). The estimates range between 0.17 and 0.27. It indicates that IPCC endorsement is enjoyed by more papers, and not only the top papers or that the distribution of citations is less skewed in AR5 sample than in AR6. Climate-economics output has expanded rapidly between 2014 and 2022, thus favouring the emergence of top papers with many citations, along with the climate question moving centre-stage in a lot of discipline, having the same effect.

Figure 4: Dynamic impact of AR5 citation



3.2.3 SR15 report

SR15 as a falsification test . If the citation premium were a mechanical artifact of the IPCC process — driven, say, by the prestige halo of any IPCC publication or by contemporaneous trends in climate research — it should appear for every IPCC product. The Special Report on Global Warming of 1.5°C (SR15, 2018) provides a direct test. SR15 covers overlapping literature and authors, yet it differs from the Assessment Reports in two key respects: it is narrower in scope (a single temperature target) and its primary audience was policymakers rather than scientists, limiting spillover into academic citation behaviour. If the citation boost is specific to the comprehensive Assessment Reports rather than generic to the IPCC brand, SR15 should show no effect.

This is precisely what I find. As shown in Figure 27 and Table 18 (Appendix E), papers cited in SR15 receive no statistically significant citation boost in the years following its 2018 release — the event-study coefficients are indistinguishable from zero across all post-event horizons, and the result is robust to restricting to economics journals and to excluding papers subsequently cited in AR6. The null SR15 result thus serves as a falsification check: it confirms that the premium documented for AR5 and AR6 is not a mechanical byproduct of IPCC affiliation, but reflects the distinctive authority and readership of the full Assessment Reports.

3.3 Heterogenity among disciplines and regions

3.3.1 Economics journals

In this section, I examine whether the citation boost from IPCC inclusion differs between economics and other disciplines. Figure 29 plots the event-study estimates from Equation (2), separately for papers published in economics journals, defined according to the CNRS classification, and those outside of it, for both AR5 and AR6.

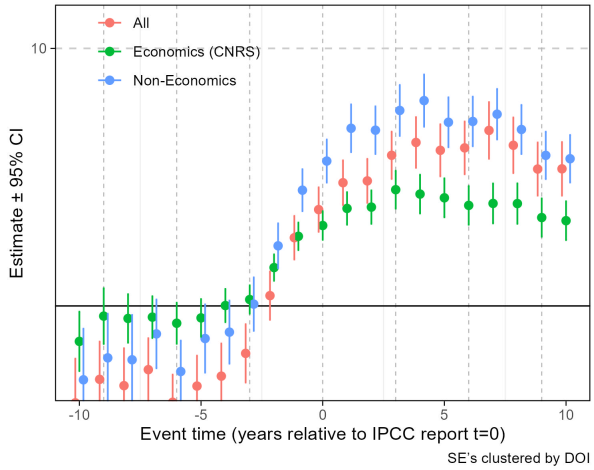
The results show that the IPCC citation effect is present for economics papers but is consistently smaller in magnitude than for papers in other disciplines. For AR6, economics articles see a modest yet statistically significant increase in citations beginning around $t = -1$

and peaking at $t = 2$, but the overall impact is clearly more limited than that observed for non-economics journals. The contrast is even more pronounced for AR5. While economics papers do experience a positive citation boost following publication, the effect plateaus much earlier, around one to two years post-release, at about +4 citation per annum, whereas the citation gains for non-economics journals is stronger from $t = -1$ and continues to rise for four to five years. Although the gap gradually narrows over time, it remains statistically significant even a decade after publication. These patterns may reflect differences in how research circulates and gains traction across disciplinary communities, or in how visible economics papers are within the IPCC's broader evidence base.

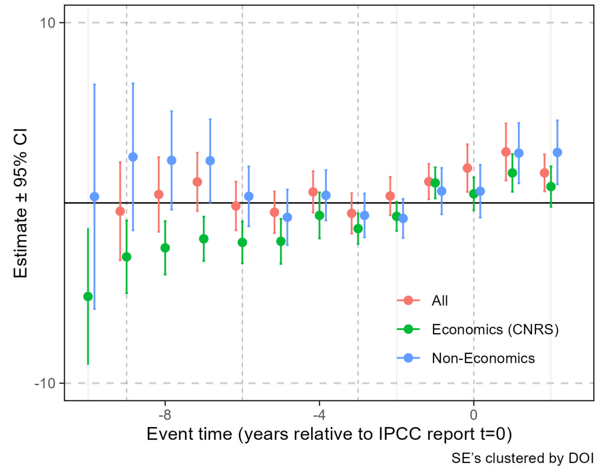
As a robustness check and alternative method, I perform a Triple Difference (DDD) adding an interaction of treat and post with the journal category (economics or not). Results are similar, (Figures 25 for AR5 and 30 for AR6).

The gap between economics and non-economics journals largely disappears when using a broader definition of economics based on the RePEc repository. For AR6, this can be seen in Figure 31 in Appendix F, and for AR5 in Figure 26 in Appendix D. Under the RePEc classification, many interdisciplinary and high-impact journals, such as Nature Climate Change, Applied Energy, PNAS, Sustainability, Energy, Nature Energy, Nature Communications, Science, and Nature are included as economics journals, even though they are excluded from the CNRS ranking. For reference, non-economics journal for REPEC include Environmental Research Letters, Journal of Cleaner Production, Global Environmental Change, and Energy Research & Social Science.

For AR5, the fact that pre-publication coefficients for economics journals are not significantly different from zero—while those for non-economics journals are negative—may point to a topic composition effect. Most economics journals in the sample are focused on environment and climate, so both treated and control papers are likely to be relevant to the IPCC. In contrast, non-economics journals like Nature or Science include many unrelated papers in the control group, which may depress baseline citation rates and inflate the apparent treatment effect. I cannot confirm this hypothesis, as I lack topic data for AR5. Interestingly, the pattern is reversed for AR6, with non-economics journals showing more stable or positive pre-trends.



(a) AR5



(b) AR6

Figure 5: Average yearly citations: AR6 & AR5 citations boost for Economics journals

3.3.2 Global North vs Global South premium

Being cited by the IPCC delivers a measurable citation dividend, but the gains are unevenly distributed. Figure 6 shows that articles written exclusively by Global South scholars receive no statistically significant boost either before or after an Assessment Report. Papers authored solely by Global North researchers earn a dividend roughly equal to the sample average (see Figure 3), while mixed teams combining Global North and Global South contributors enjoy the largest post-report surge in citations. This finding is robust to restraining the corpus to each group for the treated and the control group. For this figure I add an interaction term between event time and treatment and region, constructing a triple-difference-and-difference. The analysis performed on three restricted samples is available in Appendix F, Figure 33.

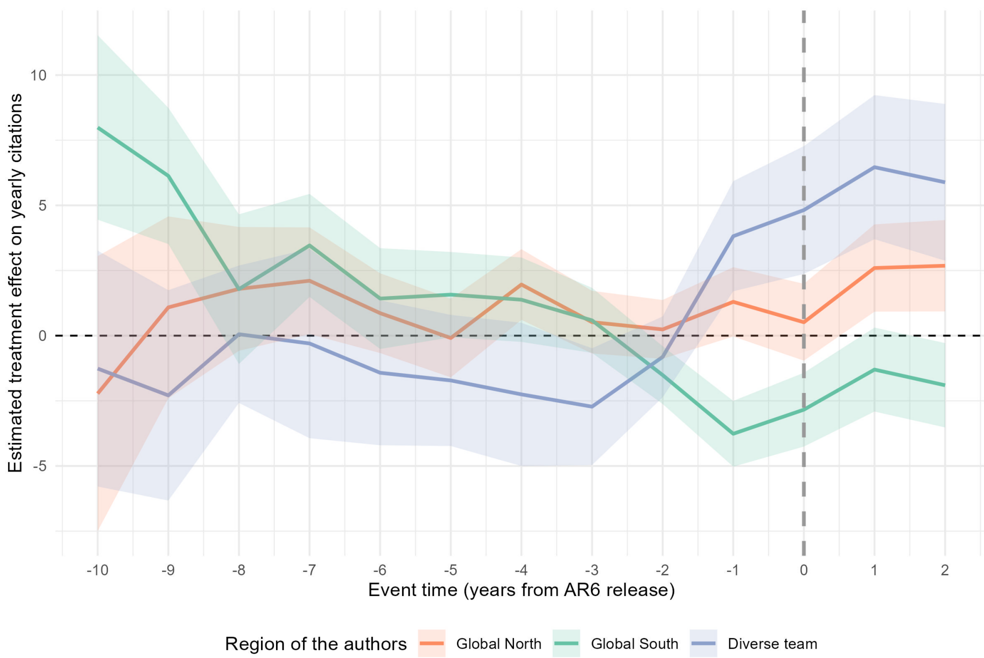
$$\begin{aligned} \text{cit}_{ijt} = \sum_{k\neq -1} \Big[& \beta_k \mathbb{1}\{\text{event\_time} = k\}_t \times \text{Treat}_i \times \mathbb{1}\{\text{Region}\}_i \; + \; \alpha_k \mathbb{1}\{\text{event\_time} = k\}_t \; + \; \gamma_k \text{Treat}_i + \xi_k \mathbb{1}\{\text{Region}\}_i \Big] \\ & + \delta \, \text{Cit3}_i + \mu_{ijt} + \varepsilon_{ijt}, \end{aligned} \tag{3}$$

One plausible explanation is scale: homogeneous Global North or South teams average just under four authors, whereas mixed teams average 8.5. The asymmetry therefore seems rooted not in IPCC selection bias as Global South–only papers make up a sizable share of the cited corpus (Table 4), but in the broader citation market, which disproportionately rewards already-visible Global North networks. As a result, the IPCC's endorsement amplifies existing visibility rather than redressing it.

Table 4: Distribution of papers by authors' region of origin

Authors' region	Papers	Share
Global North	49253	54.9%
Global South	20330	22.7%
Diverse team	20156	22.5%

Figure 6: Dynamic impact of AR6 citation grouped by the geographic affiliation of the papers authors



Note: This plot shows event-study estimates by author team composition using interaction terms. The sample is partitioned into three mutually exclusive groups: publications authored solely by Global North (GN) teams, solely by Global South (GS) teams, and mixed teams including authors from both regions. Interaction terms allow estimation of group-specific effects in a single model. Confidence intervals are computed using the delta method from the clustered variance-covariance matrix.

4 Instrumental Variable: Author Turnover

I use the quasi-random turnover of the authors team between the Fifth (2014) and Sixth (2022) Assessments Reports of the IPCC as an instrument for a paper's inclusion in the AR6. About 75% of the author team is replaced between AR5 and AR6[4] Incoming authors bring distinct disciplinary backgrounds, up-to-date bibliographies, and their own work. Author turnover is exogenous to any individual paper's intrinsic citation trajectory. I use the share_in_i, the fraction of incoming AR6 authors who had previously cited paper i. The turnover can only affect post-2022 citations through the channel of being formally cited in the IPCC report, satisfying the exclusion

[4]Robust to included the whole team working on the report, including the SPM drafting team or limiting it to Coordinating Lead Author, Lead Author, and Contributing Author.

restriction. A growing share of new comers citing a paper can only increase its probability of being included in the report, thus satisfying monotocity.

One potential concern is that incoming AR6 authors are not randomly drawn from the field but are selected partly on the basis of recent productivity and emerging prominence. If prolific newcomers systematically work on topics experiencing independent citation growth after 2018 — for instance, because they specialise in post-Paris Agreement policy mechanisms that happened to attract growing attention — then the instrument could capture topic-level trends rather than the causal effect of inclusion. Three features of the design mitigate this concern. First, I control flexibly for journal × publication-year fixed effects and pre-appointment citation stock, absorbing baseline prestige and topic-level momentum. Second, I restrict the sample to papers published before 2018, ensuring all pre-treatment trajectories are fixed prior to author appointment. Third, and most directly, the SR15 falsification test in Section 3.2.3 shows no citation boost for a contemporaneous IPCC product covering overlapping literature and authors — if independent topic trends were driving the result, they should appear there too.

The IPCC Bureau appoints rotating (coordinating) lead authors to achieve geographic, gender, and disciplinary balance as well as a renewal of the team upon self-nomination and submission through each country IPCC focal point. Decisions are driven by procedural mandates rather than by the characteritics of any study. The IPCC WGIII calendar states that the call to authors has been issued in September 2017 and authors appointed in January 2018, thus papers published in 2017 or before are exogenous to the IPCC authorship status. [5]

Figure 7 illustrates the exclusion restriction (solid line) and the two potential back-door confounders I block via sample restrictions and controls (dashed lines): (i) If a paper's author sits on AR6, they may self-cite (IPCC author → Inclusion). However, there is no direct link to citations (except if IPCC authors gain prestige, thus citations on all their previous papers, but that's doubtfull) (ii) Recency: papers published late may be doubly favoured (PublicationYear → Inclusion, Citations). I restrict to pre-2017 publications. I flexibly absorb journal, publication-year, and pre-2022 citation-stock fixed effects to block any remaining confounding via baseline prestige or recency. (iii) Popularity and quality: high quality papers are more likely to be included in the IPCC and in IPCC authors' own bibliography. I control for the citations count three years after publications.

[5]"A call for nomination of authors was sent to IPCC member governments, Observer Organizations and Bureau Members on 15 September 2017. They were asked to submit their nominations via their Focal Point by 27 October 2017 via the online portal for submitting nominations. The Bureaus of the three IPCC Working Groups met to select the author teams from the list of nominations on 29 – 30 January 2018." https://www.ipcc.ch/report/ar6/wg3/about/authors/

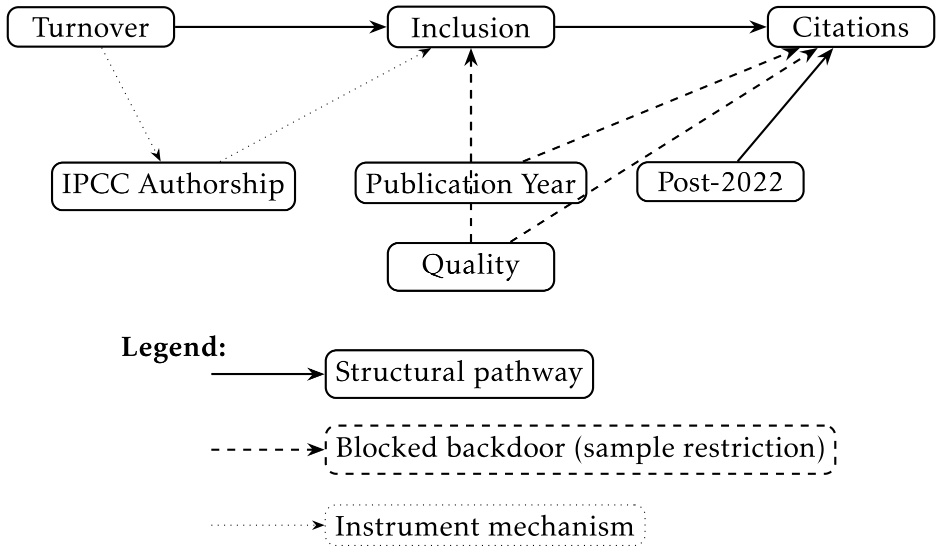


Figure 7: Causal diagram illustrating identification strategy. The main exclusion path (solid arrows) identifies the effect of *Inclusion* on post-AR6 *Citations*, using chapter-level *Turnover* as an instrument. Backdoor paths via *Quality* and *Publication Year* (dashed) are blocked through sample restrictions (restricting to paper pre-2018 and pre-authors nomination) and controls (citations count after 3 years). Instrumental mechanisms are in dotted grey lines

4.1 Variable Construction

For all authors of AR5 and AR6[6], I fetch all the papers they have been an author in from 2000 to 2017. I then fetch the references present in these papers.

For each paper i, let

$$\text{share\_in}_i = \frac{\#\{\text{new AR6 authors who cited } i \text{ before 2018}\}}{N_{\text{new}}},$$

where $N_{\text{new}} \approx 0.77\,N$ in AR6. In details, $N_{\text{new}} = \tau N = 408$ is the number of new authors in AR6, with a turnover rate $\tau = 0.77$ and total number of authors $N = 527$.

For each paper i, treatment is a binary indicator of whether it is cited in the AR6.

This design belongs to the growing class of composition-based instruments (Bagues et al., 2017; Autor et al., 2013). Like those studies, I exploit procedural reshuffling—in our case a 75% turnover of IPCC chapter authors mandated by Bureau quotas—to generate exogenous variation in the probability that a study is referenced. This design mirrors judge-assignment instruments used in legal and policy contexts: just as randomly rotating judges shift the probability a case is heard or upheld, author turnover shifts the probability a paper enters the citation record, holding its quality and topic constant. However, unlike judge-leniency designs (Galasso and Schankerman, 2015; Kling, 2006) or child investigator tendency to resort to foster-care (Doyle Jr.,

[6]Including all Coordinating Lead Author, Lead Author, Chapter Scientist, Contributing Author, Coordinating Editor. Including or excluding drafting Author working only on the Summary for Policy Makers does not change the results.

2008). As in these papers, I compute a behavioural 'track record' of citing a certain paper. In leniency papers the random draw is which judge you get; in Bagues it is which gender mix; in Autor–Dorn–Hanson it is industry mix measured before China's WTO shock; in this case it is which scholars the IPCC Bureau rotates in for AR6, a process governed by quota rules (region, gender, discipline) and self-nominations.

4.2 Empirical strategy

I consider the treated and control group of the AR6 report (see Table 2), that is more than 300k observations and 40k unique articles. I select only these papers published in 2017 or before.

By construction our instrument meets all IV requirements: it is strongly correlated with AR6 inclusion (relevance), uncorrelated with other citation shocks (exogeneity), affects citations only through inclusion (exclusion), and is weakly monotone in its impact on treatment

Together, the shift–share instrument satisfies (i) relevance, with an unequivocally strong first stage; (ii) exogeneity, since author appointments are predetermined and uncorrelated with paper-level shocks; (iii) exclusion, as turnover cannot affect later citations except through formal inclusion; and (iv) monotonicity, because more incoming fans cannot diminish inclusion probability. This ensures that our 2SLS captures a clean Local Average Treatment Effect for the marginally included studies.

First stage (paper/doi level):

$$\text{Inclusion}_i = \alpha + \beta\,\text{share\_in}_i + \gamma \mathbf{X}_i + \delta_y + \varepsilon_{ic},$$

where $\mathbf{X}_i$ captures journal prestige, paper quality (pre-inclusion citation trajectory) publication year, and topic fixed effects. δ_y is a year fixed effect. I expect $\beta > 0$ if fresh team cite more outside work.

Second stage (paper level, 2SLS):

$$\text{yearly-citation}_{it} = \rho + \theta\,\widehat{\text{Inclusion}}_i + \lambda \mathbf{X}_i + \delta_y + \mu_{it}.$$

4.3 Results

Table 5 presents the 2SLS regression along with the first stage statistics. Given the noise introduced by the first stage, despite its strength, the log scale allows to reduce the influence of outliers and highly cited papers. Thus, columns (3) and (4) are my preferred specifications. Columns (2) and (4) try to reduce noise by grouping together the journals which are not in the top 10 of most represented journals and years in a 3-year windows. It marginally improves the performance but not enough to make the level specification to be significant.

Our preferred IV estimate is a semi-elasticity of 0.513 on log(1+Yearly Citations), implying that the marginal paper whose inclusion is shifted by an additional incoming AR6 author-citer experiences roughly a 67% increase in its annual citations.[7] Back-of-the-envelope, given an median of 11 (the mean is 24) citations per year, this translates into roughly +7 additional citations annually.

[7] From the coefficient $\theta = 0.513$ on $\widehat{\text{Inclusion}}_i$, the semi-elasticity is $\exp(0.513) - 1 = 0.67$

Table 5: 2SLS AR6 WGIII Report Impact on Yearly Citations instrument by author turnover

Dependant Variable	yearly_cit		log(1 + yearly_cit)	
	(1)	(2)	(3)	(4)
fit_treat × post	21.9	20.9	0.5***	0.5***
	(19.5)	(20.5)	(0.1)	(0.1)
cit3	0.3***	0.3***	0.0***	0.0***
	(0.0)	(0.0)	(0.0)	(0.0)
Num.Obs.	328 575	328 575	328 575	328 575
R2	0.640	0.629	0.558	0.407
R2 Within	0.463	0.613	0.113	0.295
Std.Errors	by: doi	by: doi	by: doi	by: doi
First-stage - Dependant variable treat:post				
share_in:pos.	101.7***	102.8***	101.7***	102.8***
	(7.15)	(7.12)	(7.15)	(7.12)
cit3	1e-05*	7e-06+	1e-05*	7e-06+
	(0.00)	(0.00)	(0.00)	(0.00)
F-stat	202.4	208.4	202.4	208.4
Journal FE	✓	✓(bin)	✓	✓(bin)
Year FE	✓	✓(bin)	✓	✓(bin)
Publication Year FE	✓	✓	✓	✓
Time Since Pub FE	✓	✓	✓	✓

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

Clustered standard errors at the paper (DOI) level.

Each column represents a different specification.

I can then conclude that the inclusion into the IPCC has a causal boost on citations, net of paper quality, journal prestige and lifespan of the paper.

The fact that our two-stage least squares estimate implies a +7 citation bump, while the raw difference-in-differences on treated vs. control yields only +4 (see Table 3 boils down to the Local Average Treatment Effect interpretation (LATE) of IV vs Average Treatment Effect on the Treated (ATT) of the event study,

$$\begin{cases} \text{ATT} = E[\,Y_i(1) - Y_i(0)\,|\,C_i\, = 1], \\ \text{LATE} = E[\,Y_i(1) - Y_i(0)\,|\,C_i(1) \neq C_i(0)], \end{cases} \tag{4}$$

with $C_i = 1$ is the condition that the paper is indeed IPCC cited. Y_i is the yearly citation.

The event-study ATT lumps together headlines papers that would be cited regardless of turnover and compliers (papers only cited when turnover is high). These papers enjoy a large baseline citations and thus dominate the ATT. By contrast, LATE isolates exactly those papers whose AR6 citation status pivots on author turnover ("compliers"), or more niche papers, and these marginally included studies appear to enjoy larger citation gains. In other words, turnover not only endogenously selects high-impact work into the report, but it generates especially large downstream visibility for the subset of papers whose gatekeepers' arrival makes the decisive difference.

Note that I also explored a residualised 'loss of champions' instrument, i.e. the share of pre-2018 AR5 authors who cited each paper but did not return in AR6. However, this 'leavers' shock proved to be a very weak predictor of post-2022 inclusion (F≈1.2), and so I cannot rely on it for identification. An hypothesis is that the popularity with leavers is highly correlated with AR5 incumbent and AR6 new comers, thus indicating the paper's popularity. Using the residual of the linear regression of the share of citers among leavers on the share of citers among the whole AR5 has too little variation to be exploitable.

5 Self-Citation and Author Involvement

I examine self-citation for two main reasons. First, to assess whether contributing to the IPCC is associated with a measurable citation benefit for the authors' own work. Second, because self-citation poses a potential identification threat: if authors systematically cite their own papers, then inclusion in the IPCC reference list is no longer exogenous.

Self-citation analysis is complicated by the fact that many contributors hold multiple roles across chapters within the same report. In AR6, for instance, three individuals are involved in as many as eight chapters, and several others contribute to six or seven. Of the 953 named authorship positions in AR6, these are held by 561 unique individuals. Among them, 170 are active in more than one chapter, while 391 appear in only one. Coordinating Lead Authors (45 in total) and Drafting Authors for the Summary for Policymakers (83) are involved, on average, in approximately four chapters. Lead Authors (258) and Contributing Authors (465) are active in roughly 2.5 chapters each.

This complex authorship structure creates a nontrivial overlap between citation and authorship networks, which I address directly in the next section.

Approximately 19.6% of references cited in AR6 include at least one author who also contributed to AR6 itself. In comparison, only 15.3% of references include an AR5 author, and

11.2% include an SR15 author. Overall, 28% of references feature an author who participated in the authorship of at least one of the three reports (Table 6).

Table 6: Summary self-citation statistics of AR6 WG III

Nb AR6 references	Share AR6 aut.	Share AR5 aut.	Share SR15 aut.	Share any IPCC aut.
15130.00	0.20	0.15	0.11	0.28

Table 7: Share of IPCC authors involved in the AR6 WGIII references

IPCC AR6 role	Share of unique refs with IPCC author	Share of refs with IPCC author	Share of refs with chapter author
Coordinating Lead Author	0.05	0.07	0.02
Drafting Author	0.07	0.10	NA
Editorial Team	0.01	0.02	NA
Lead Author	0.14	0.18	0.05
Contributing Author	0.16	0.21	0.08
Coordinating Editor	0.00	0.00	NA
Review Editor	0.01	0.01	0.00
Chapter Scientist	0.01	0.01	0.00
No role	0.80	0.76	0.87

Note: Column (1) reports the share of unique references with at least one author involved in AR6. Column (2) uses non-unique references (i.e., those cited in multiple chapters are counted repeatedly). Column (3) shows the share of chapter-specific references with at least one author involved in the citing chapter. The top rows show shares by author role. The last row, *No role*, indicates references where no author is involved in the IPCC (cols. 1–2) or in the citing chapter (col. 3). Columns do not sum to one, as one author may appear in multiple roles in different chapters and different authors can hold different role in the same chapter.

Table 7 documents the extent to which papers cited in AR6 WG III are written by the report's own authors. I distinguish three units of observation: (i) *unique references* (each paper counted once), (ii) *reference–chapter pairs* (so that a paper cited in two chapters is counted twice), and (iii) *chapter-specific links* (does the citing chapter include at least one author of the cited paper?).

There is a large IPCC author involvement in the references, but only modest chapter-level overlap between IPCC and papers authors. Among unique references, 19.6% contain *any* AR6 author, and 15.8% contain a *Contributing Author*. For reference–chapter pairs (non-unique references) the shares rise to 24.5%, reflecting multiple citations of the same papers. Only 7.9% of reference–chapter pairs involve a CA who also serves on the citing chapter; 87.3% have no author–chapter link whatsoever. In other words, barely one citation in twelve can be labelled a "within-chapter self-citation."

Column totals do not add to unity because multi-authored papers can include several IPCC authors with heterogeneous roles; for instance, Hilaire et al. (2019) is cited in AR6 Chapter 1, and is co-authored by both a Coordinating Lead Author and a Contributing Author for this very chapter. It means that for some papers, the self-citation could be from two authors, meaning 12.7% are cited in a chapter where one of their authors has a role. The sum of the rows with role gives 15.5% because some papers have more than one author with a role. Note that anyway, I have no way of saying that the authors directly cited themselves, a chapter is a large body of text, where multiple people co-write independently some part.

However, I can notice that the distribution of references which one authors is involved in the IPCC is not random. Half of the references of which an author is involved in the AR6 is precisely involved in the chapter in which they are cited in (24.4% in total, 12.7% for the very same chapter). It also shows at the role-level, about 15% of papers (unique) have a contributing author as an author, representing 20.6% of non unique references but still 7.9% happen to be a contributing author in the very own chapter they are cited in. It means that this citations by an aR6 authors are not in any chapter (1/22=4.5%). means it's not random: two explanation. Either self citation, or specialised expertise. Two, not mutually exclusive, mechanisms could rationalise this pattern: (i) deliberate self-citation by chapter authors; and (ii) genuine expertise—the same researchers who shape the chapter also produce canonical work that merits citation irrespective of authorship.

Matching of AR5 and AR6 content To answer this question, I use the previous AR5 report authorship as as most of the authors change in between reports. The selection functions in 3 steps: i) candidates for Coordinating Lead Authors (CLA) and Lead Authors (LA) apply to their national IPCC focal point which gathers the applications of its nationals; ii) the IPCC bureau selects CLA and LA from these applications based on expertise ensuring an appropriate balance of gender, country (Global South and Global North), and experience in the IPCC (seasonned and new members); iii) the CLA and LA select the Contributing Authors also ensuring a range of expertise and a balance of gender, regions, and experience. The key insights is that expertise alone is not the only driver, meaning that perfectly apt candidates are not selected or do not reapply (e.g. to ensure renewal of the IPCC authorship base or to dedicate their time to other tasks, respectively). But the fact these are not anymore IPCC authors does not erase their expertise and their relevance to the reports, hence the citation of their work should continue. I use this renewal to test whether there is a bias of self-citations.

I match each AR6 chapter with a AR5 chapter, based on the similarity of the content of the whole chapters. I use the TF-IDF (term frequency-inverse document frequency) to compare the content of each pair of chapters from AR6 and AR5. This method, allows to compute the frequency of each word in each chapter. Some words will appear frequently in some chapters (e.g. ”icev” for the Transport chapter (chap10) or ”renov...” for the Building chapter(chap9)). The idea of the reweighting is to give more weight if they are specific to this chapter relative to the whole document (e.g. emissions might be less relevant in the IPCC report, since it appears virtually everywhere). I then compute the cosine distance between the reweighted vector of words for each chapters in AR6 and AR5 to find the best match. See Appendix B for the details of the procedure.

For some chapters, the match is easy, as there is one clear candidates. It is the case for the thematic chapters: Building, AFOLU, Transport, Industry, Energy systems. For the transversal chapters: Mitigation Pathways, Emissions trends. I may have several candidates (see Figure 16).

I first compute the share of within-chapter self-citation for each chapter of the AR6. I then compute what would this share of within-chapter self-citation would be if the authors team had been the same as for the equivalent chapter in the AR5, 8 years before. If the two shares are very different, it might indicates

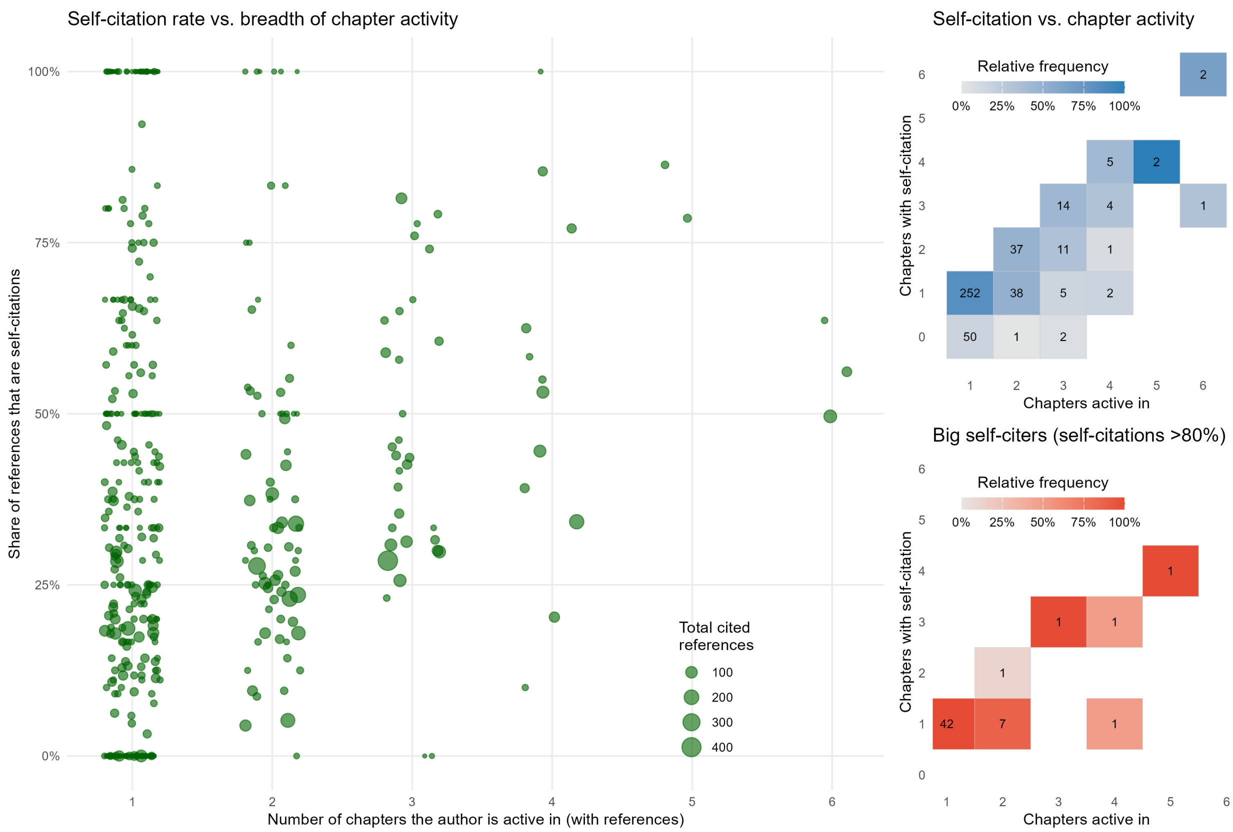
Common authorship across assessment cycles : Approximately 21% of AR6 authors also contributed to AR5. Among them, 84 individuals participated in the same chapter across both reports—representing around 60% of all repeated authors and 12% of the total AR6 author pool. Figure 17 shows the chapter-level mapping of shared authorship. This supports the validity of our text-based chapter matching approach. The highest overlap is observed in Chapter 10 on Industry, where 34% of AR6 authors had already contributed to the same chapter in AR5.

AR6 chapters display a higher self-cite rate than their AR5 counterparts. Across nearly every chapter, the fraction of citations written by an author of that chapter is larger in AR6 than in AR5.

But true author "carry-over" is low. Only about 15% of the AR6 chapter team are holdovers from the matched AR5 chapter, yet one can see self-cite rates of 35–40% if I test against the old team. The fact that AR6 authors frequently cite papers by the previous cycle's experts—despite low overlap—suggests that IPCC inclusion confers a signalling endorsement on earlier work, beyond narrow within-chapter self-citation. It means that expert endorsement dominates pure self-citation.

Figure 8 illustrates key patterns in self-citation behaviour. In the left panel, I observe that authors with the largest number of cited references are typically not among the highest self-citers. In contrast, high self-citation shares are often associated with authors who are active in only one chapter and have relatively few total citations. The right panel shows that self-citation breadth tends to increase with chapter involvement: the concentration of darker tiles along the diagonal suggests that authors frequently self-cite in every chapter where they are active, with little self-citation occurring beyond their direct contributions.

Figure 8: Self-citation distribution in AR6



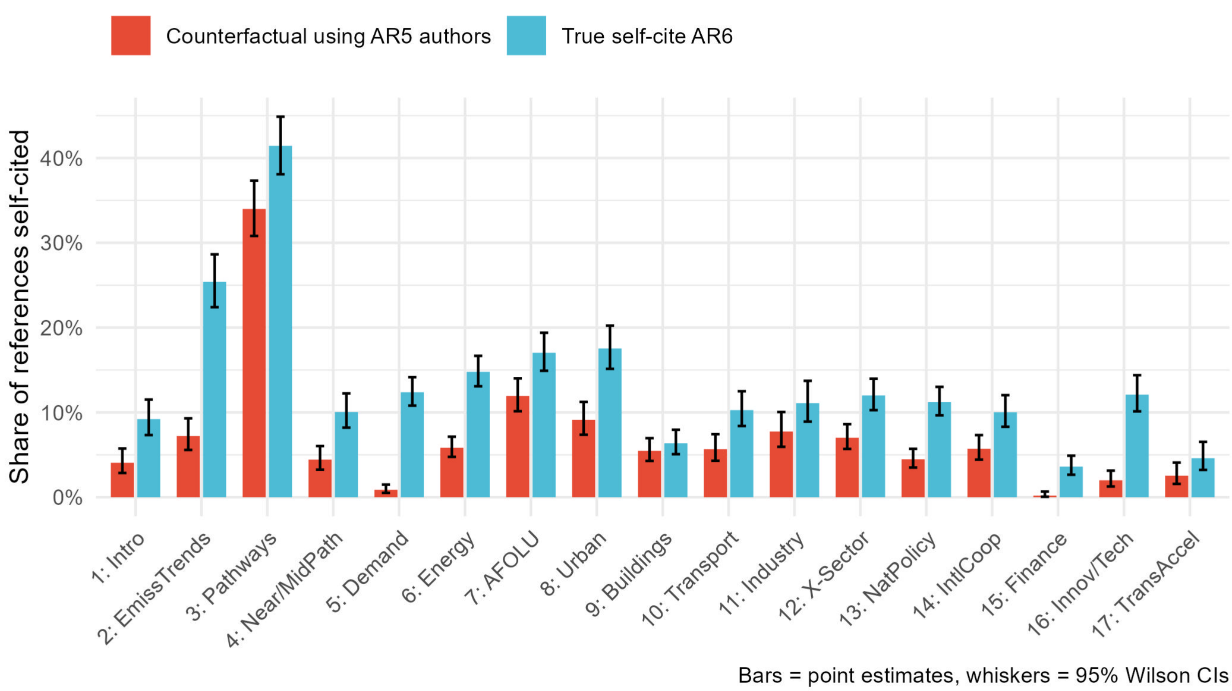
Comparing AR6 and AR5 To gauge the precision of the chapter–level self–citation shares I treat each cited reference as a Bernoulli draw—success if at least one author of the citing chapter appears on the reference, and failure otherwise. Let x_c denote the number of such successes in chapter c and n_c the chapter's total references. Under a binomial model the maximum–likelihood estimate is $\hat{p}_c = x_c/n_c$. Because several chapters cite only a few hundred papers, I report Wilson (score) 95 % intervals (instead of the more classic Wald interval)

$$\hat{p}_c^{\mathrm{W}} \pm \frac{1.96}{1+1.96^2/n_c}\sqrt{\frac{\hat{p}_c(1-\hat{p}_c)}{n_c}+\frac{1.96^2}{4n_c^2}}, \qquad \hat{p}_c^{\mathrm{W}} = \frac{\hat{p}_c + 1.96^2/(2n_c)}{1+1.96^2/n_c}.$$

A caveat is that reference-level outcomes are not strictly independent: the same researcher can co–author many papers, inducing positive within–chapter correlation and thus understating true sampling uncertainty. Consequently, the Wilson bands should be viewed as a visual guide—useful for spotting gross differences between AR6 and the AR5 counterfactual.

Figure 9 shows that, for most chapters, the observed level of self–citation in AR6 significantly exceeds what would be expected had the AR6 author team been identical to that of AR5. This suggests an additional layer of self-citation beyond mere author expertise.[8] Notably, however, the difference is not statistically significant for several highly specialised sectoral chapters—*AFOLU*, *Buildings*, *Transport*, and *Industry* – where the authorial match between AR6 and AR5 is particularly strong. Yet even in cases with similarly high continuity, such as the *Energy* and *Urban* chapters, self–citation in AR6 remains significantly higher, underscoring that the observed effect cannot be attributed solely to poor chapter matching. I perform the same analysis for AR5 chapters, Figure 23 in Appendix D, showing that the level of self-citations seems to be smaller for AR5 than for AR6.

Figure 9: Chapter-level self-citation shares in AR6 and in equivalent AR5 chapters



For chapter 3, I see that many authors of AR5 are cited in AR6 (even if low overlap, about 15%), which is why I cannot conclude there is a significant self-citations.

Citation boost impact I examine the identification implications of the citation premium and find that the effect remains robust. Because the majority of IPCC-cited papers share no authors with the citing chapter, the boost documented in the main text cannot be explained solely by within-chapter self-citation. To test this directly, Appendix F.1 reports event–study estimates excluding all such self-cites. The magnitude of the effect falls ever slightly: the estimated annual citation gain drops from +2-3 to approximately +1.5–2.5, but remains statistically significant.

[8]Note that I cannot take into account retirement or decrease of productivity of AR5 authors and new young AR6 authors.

The event–study plot reveals a negative pre-trend for the treated group around $t = -7$, with a dip of about 10 citations relative to the control group. This decline may partly reflect differences in publication year or journal composition between the full and restricted samples—factors that could plausibly account for the entire reduction in the estimated effect. Nevertheless, the persistence of a significant post-treatment effect supports the interpretation that the citation premium reflects broader endorsement by the IPCC process, not merely author self-selection.

I re-estimate our main event-study specification by introducing an interaction term to isolate the effect of within-chapter self-citation:

$$\text{cit}_{ijt} = \cdots + \phi \cdot \mathbf{1}\{\text{self\_cite}_{ij}\} \times \text{Post}_t + \varepsilon_{ijt}$$

where cit_{ijt} denotes the citation count for paper i in chapter j at time t, and Post_t is an indicator for the post-AR6 period. The binary indicator $\mathbf{1}\{\text{self\_cite}_{ij}\}$ captures whether any author of paper i is also an author of chapter j. The coefficient ϕ tests whether such self-cited papers receive an additional citation boost relative to non-self-cited papers in the post-treatment period.

The coefficient Φ is not statistically significant, but the citation boost of IPCC inclusion is marginally lowered to about +1-2 citations per year. I report the event-study with the self-citation dummy interaction with the post AR6 variable and the DiD estimate with the same variable in Appendix F.1 – Figure 21 and Table 13.

6 Provenance of citations

In this section, I examine whether IPCC-affiliated scientists—whether chapter authors, same-chapter contributors, or reviewers—disproportionately drive the citation boost observed for AR6-referenced papers. I estimate logistic mixed-effects models to assess whether the share of citations attributable to IPCC authors (or subcategories such as same-chapter contributors or reviewers) changed significantly following the publication of the IPCC AR6 report.

Model Specification: For each cited paper-year observation, I model the probability that a given citation originates from an IPCC-affiliated individual using the following specification:

$$\text{logit}\left(\Pr[\text{IPCC citation}]\right) = \alpha + \beta_{\text{pre}} \cdot \text{time\_pre} + \beta_{\text{post}} \cdot \text{time\_post} + \gamma \cdot \mathbf{1}\{t \geq 2022\} + u_i + v_j + w_k,$$

where time_pre and time_post represent linear trends before and after the event year (2022), and u_i, v_j, and w_k are random intercepts for cited paper (source_doi), journal, and time since publication, respectively.

The results show that the observed citation boost for AR6-referenced papers is not primarily driven by increased activity from IPCC-affiliated individuals. Citations from IPCC reviewers exhibit no statistically significant change after the report's release; the estimated post-event coefficient is small and imprecise ($\hat{\gamma} = -0.014$, $p = 0.10$), and both pre- and post-trends are weakly positive. For IPCC authors more broadly, the post-2022 trend is negative and statistically significant—for instance, $\hat{\beta}_{\text{post}} = -0.048$ with $p < 0.001$—indicating a relative decline in their share of citations. This decline is even more pronounced among same-chapter authors, whose post-2022 trend reaches approximately -0.11, again highly significant. Notably, there is no evidence of an upward trend in their citation activity prior to the report. In the context of logistic regression, these coefficients represent changes in log-odds: for example, a coefficient of -0.113 corresponds to a 10.7% reduction in the odds that a citation comes from a same-chapter author. These estimates account for random heterogeneity across cited papers, journals, and citation age, and together suggest that the citation gains documented earlier are not the result of insider reinforcement, but rather reflect broader diffusion of IPCC-endorsed knowledge.

Model Comparison and Implications: While models are estimated separately for each group (reviewers, IPCC authors, same-chapter authors), the consistent pattern across specifications supports a robust interpretation: the share of citations from IPCC-affiliated individuals did not increase following AR6. Instead, it remained flat or declined, despite the total number of citations to AR6-cited papers rising during the same period (as shown in the event study).

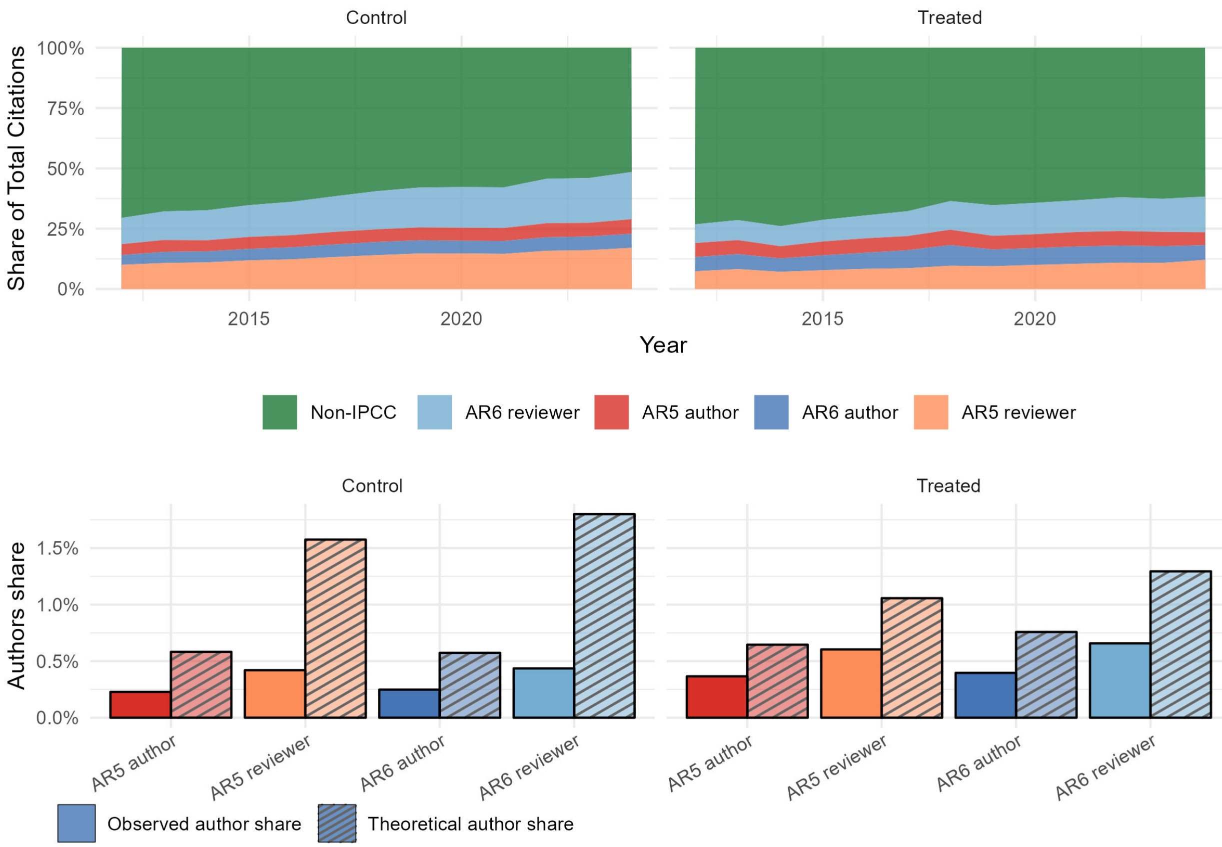
This suggests that the citation boost observed for AR6-cited papers was not primarily driven by self-citation or strategic promotion by insiders. Rather, it is more consistent with an external endorsement or visibility effect — that is, non-IPCC authors increasingly cited these papers following the release of the report, reflecting broader diffusion or attention.

I show that IPCC-linked authors make up for a significant share of citations of both the IPCC referenced papers and the control group (resp. 38.3% and 48.5% of the 2024 total citations received). First conclusion is that the citations are still primarily coming from papers where none of the authors have had any link to the IPCC since 2018, without much change between 2012 and 2024. Hence, any boost in citations I see cannot be only imputable to the IPCC authors citing these papers after they have included it in the report or because they have links to the report. Second, the share of IPCC involved scientists is greater in the citation pool of the control group (where it's not only climate papers, from general Econ or generalist journals such as Nature or Science). Hence the probability that a citation is coming from an IPCC author is actually lower for the IPCC-cited references than any other equivalent paper.

In figure 10, I report three related metrics per category: (1) the percentage of papers that have at least one author in this category (upper panel), and (2) the percentage of all author positions filled by authors in that category (bottom panel, solid colour). Since papers have on average 9 authors, one expects the share of authorships to be notably lower than the share of papers. Under a simplistic random-assignment model, if q is the share of IPCC-related authors, the probability a random paper of size $n = 9$ has ≥ 1 author in the category is $1-(1-q)^n$.[9]. I plot this theoretical share of authorships in dashed colours in the bottom panel, average across 2012-2024 (since not all authors are active every year). It shows that the share of AR6 authors implied in citing papers is low, about 0.4% of the total pool of authors (of the treated group), but to explain their citation share, it would need to be 0.75%. They are over-represented. Since it is exaggerated in the control group, I can safely conclude their over-representation is because of their focus on these topics, their prolific production rather than them citing mostly the papers they have themselves included in the IPCC AR6 report, or because they have access to it. There is truly an endorsement effects for authors outside of the IPCC-bubble.

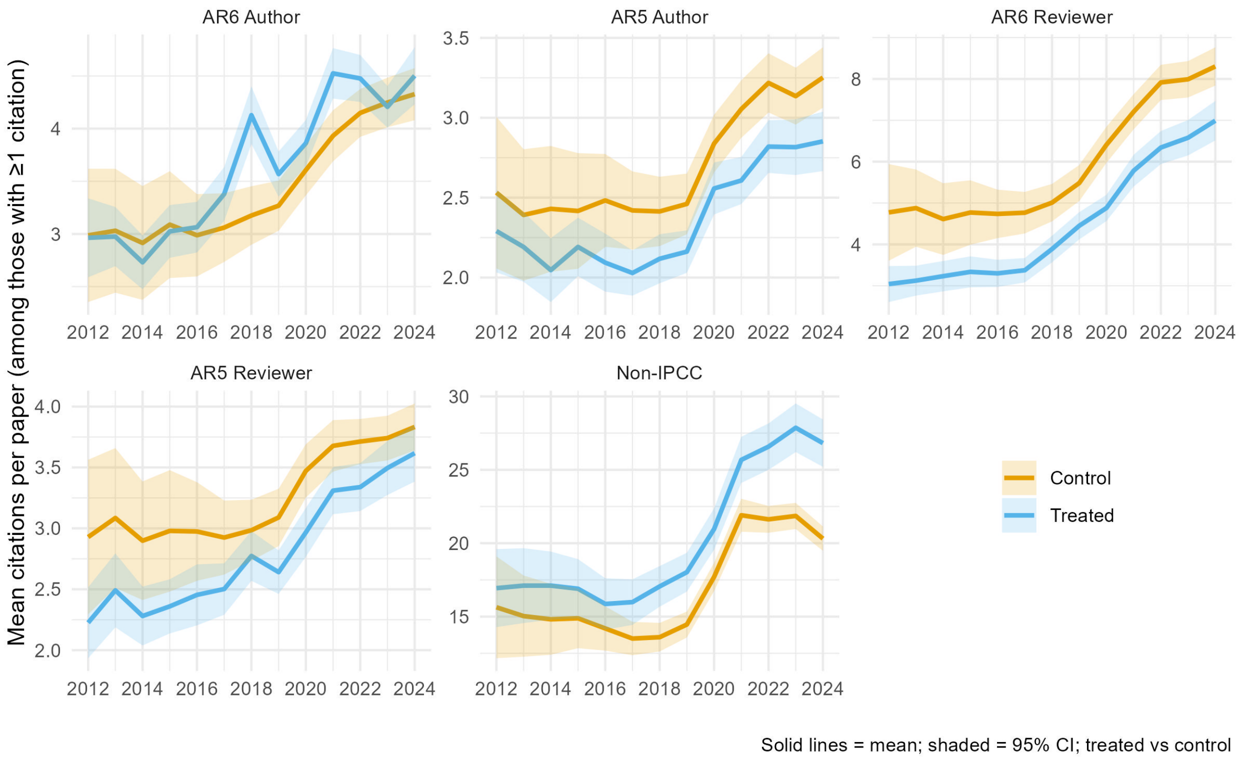
[9] The probability that none of the 9 authors has linked with the IPCC under a random assignment is $(1-q)^n$, hence the probability to have at least one is the opposite probability $1-(1-q)^n$.

Figure 10: IPCC-Linked citations and authorship among papers citing AR6 references



Avg authors per paper ≈ 9.22. Theoretical y = 1 - (1 - share_citations)^9.22. The categories of authors are exclusive, some categories takes precedence over the others, in this order, AR6 author > AR5 author > AR6 reviewer > AR5 reviewer., The share of citation reflects the fact that a least one author from this category. The share of authors is the share of uniques authors active this year.

Figure 11: Average Citations per Paper Over Time, by IPCC Author Category



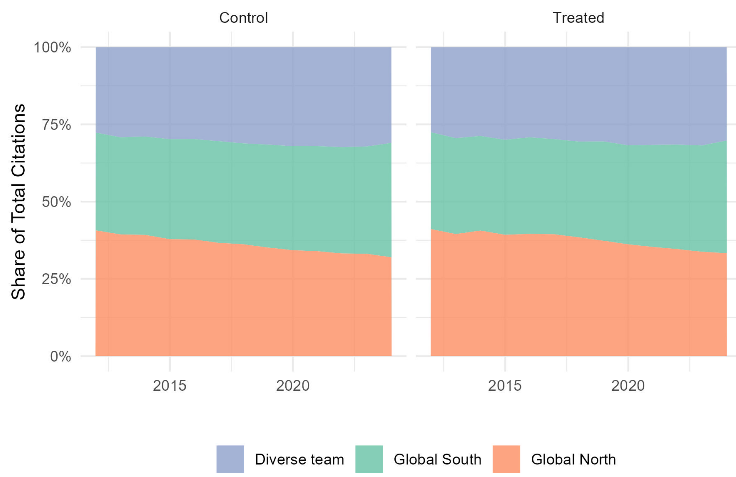
Note: to get the number of Figure 2 one needs to aggregate up the numbers of all 5 graphs, the categories are exclusive. Since the data are not identical (here I sum up individual citations whereas in 2 I get the citation count per year directly. Comparison at the paper level sometimes show slight discrepancy.One can the resulting figure in appendix, Figure 35

I plot it also for aggregated ”IPCC-related authors” in Appendix, see figure 34.

6.0.1 Global North vs Global South

Having established in the previous section that only publications authored by scholars from the Global North appear to benefit from the “IPCC boost”. Is this effect attributable specifically to authors based in the Global North, or is it also observable among authors from the Global South?

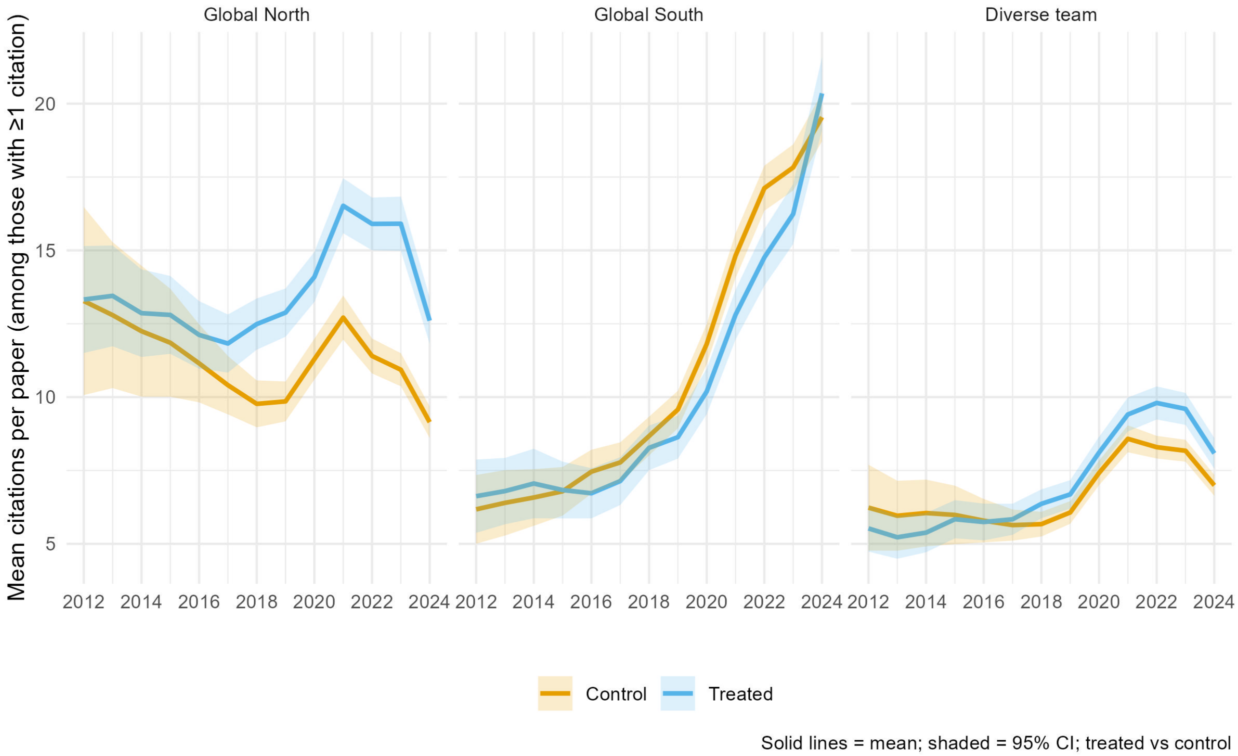
Figure 12: Share of citations received by AR6 references by region of the institution of the authors of the citing papers



The citations are first coming from Global North (could be explained by better access to journal behind paywalls) while citations from Global South increase later on[10]. Global South and diverse team of authors from both GN and GS do not seem to have changed patterns between control and treated in 2020-2022. But there is a clear increase of citations from Global North Authors in 2020.

[10]see Figure 36 in Appendix) that shows that the Global North and Global South contribute the same number of citations 3-4 years after the publications of the papers, but that up until then GN is contributing more while GS is increasing steadily in both control and treated groups.

Figure 13: Average Citations per Paper Over Time, by region of the institution of the authors of the citing papers



7 Citation additionality

This section tests whether papers cited by the IPCC follow a different citation trajectory than comparable work. If IPCC endorsement shifts attention, the ensuing citation premium may arise from:

(a) an expansion of the field's overall attention; or

(b) a quality-improving reallocation of citations away from weaker studies.

Both these mechanism would be welfare-augmenting, but it might also be the case that there is no quality gains in the reallocation, the mechanism being in aggregate zero-sum.

I analyse 7 000 IPCC references and a matched control group. For each paper I retrieve OpenAlex topic codes. The IPCC set spans 508 primary topics; the control set spans 2 440.

Because the aggregate effect starts in 2019–20, I guard against contemporaneous shocks—most notably COVID-19 and the emergence of new research lines such as AI. I exclude all COVID-related topics, the broad fields *Biochemistry, Genetics and Molecular Biology*, *Immunology and Microbiology*, *Medicine*, and *Computer Science*, as well as the specialised topics *Computational*

Drug Discovery Methods, *Algorithms and Data Compression*, *Lysosomal Storage Disorders Research*, *Advanced Chemical Physics Studies*, and *Topological Materials and Phenomena*.

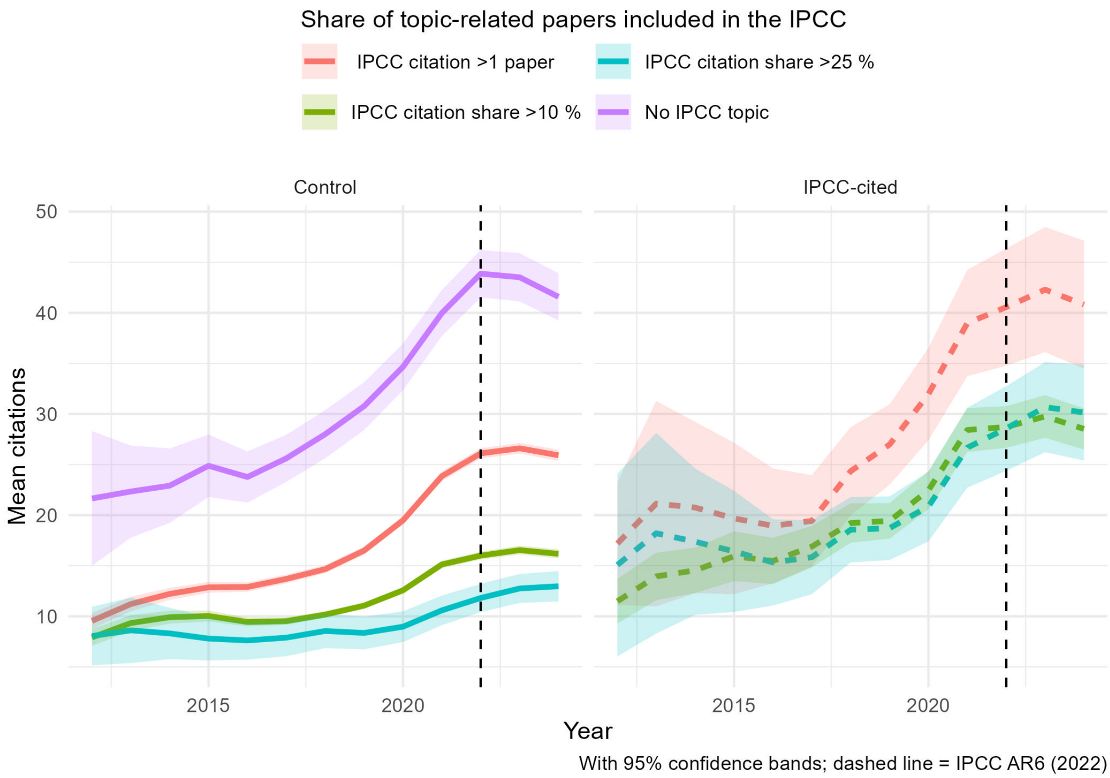


Figure 14: Yearly citations average and 1.96 × standard error for IPCC included topics (depending on the intensity) and other topics

7.1 Citation patterns around IPCC endorsement.

Figure 14 shows yearly citations for papers that *are* (solid lines) and *are not* (dashed lines) cited in AR6, split by the share of papers in the topic that receive an IPCC citation. A few patterns stand out. First, topics that never appear in the report (purple solid line, left panel) attract more citations overall than topics that do, illustrating that the topics covered by the IPCC are not the trendiest (thus reinforcing further all our analysis by making the IPCC selection exogenous). Second, average citations rise steadily in all groups up to 2022 as new cohorts enter the data and existing cohorts age and accrue citations; treated and control series grow at similar rates (similar pre-trends), so this mechanical expansion does not mask treatment differences. Third, the post-2022 citation jump is largest when the IPCC cites only one or two papers in a topic (red "> 1 paper" bin) and much smaller when the IPCC cites 10–25 % of the topic's output (green and blue lines). This is consistent with a simple "scarcity" story: the fewer the endorsed papers, the bigger their gain as they might become "reference" paper.

7.2 Reallocation rather than expansion.

For non-cited papers (left panel) citation growth slows most in topics that receive the heaviest IPCC attention, yet continues in never-cited topics. Among the cited papers themselves (right panel) the extra citations concentrate on the handful endorsed in low-share topics, while being spread thinly in high-share topics. Together, the two panels suggest a reallocation of scholarly attention: IPCC endorsement shifts citations towards the highlighted papers without increasing the total pool of citations in the field. Whether this shift speeds up the diffusion of key results or sidelines useful alternative work is a question I return to in a following section .

7.3 Dose–response evidence of citation crowding-out.

Figure 15 reports coefficients from

$$\text{citations}_{it} = \sum_{k=-10}^{+2} \beta_k \Big[\mathbf{1}\{t = k\} \times \text{IPCC-share}_{g(i)} \Big] + c_{it} + \gamma_i + \lambda_t + \varepsilon_{it},$$

where IPCC-share$_{g(i)}$ is the fraction of papers in topic $g(i)$ that are cited in AR6 over the time-windows (2012-2019), and the specification absorbs journal, field and subfield fixed effects, publication-year effects, a paper-age (time-since-publication) profile, and the citations received 3 years after publication (c_{it}). Standard errors are clustered by DOI.

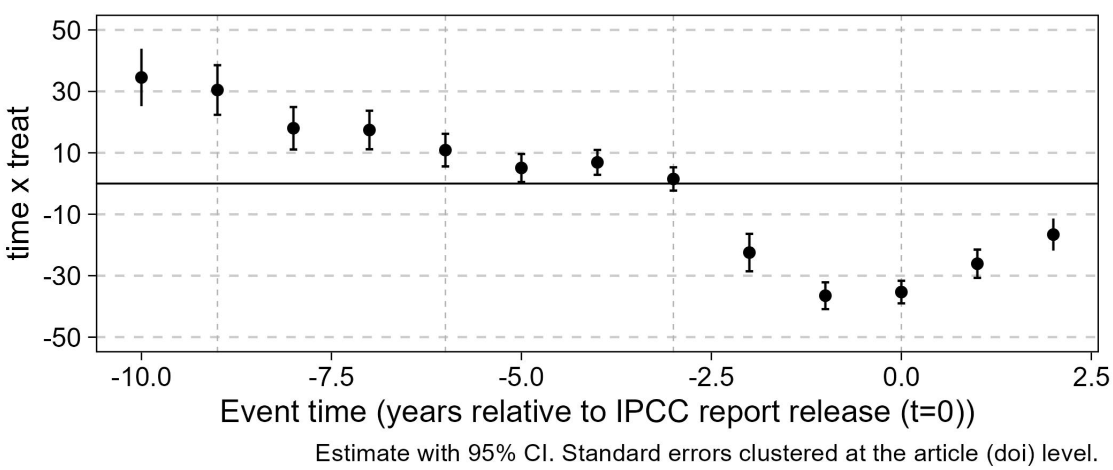


Figure 15: Citation dynamics of IPCC-included topics vs other topics for papers never included in the IPCC

Three features stand out. After conditioning on journal, field, subfield, cohort, and paper-level quality, I still see that topics with higher IPCC share had systematically higher citation trajectories prior to 2022: oefficients ($k = -10, \ldots, -3$) are positive.

A hypothesis to explain that papers pre-AR6, papers in IPCC topics, is that these topics are central for the journal I consider (Energy Policy, Nature Climate Change), thus they get more citations naturally compared to more marginal topics in these journals. The journal fixed effect takes care of the citation-premium associated with large interdisplinary journals, e.g. Nature and Science, which explain why I find that papers on IPCC-topics get more citations than other topics *when corrected for all fixed effects* while Figure 14 show that Non-IPCC topics are more cited in absolute numbers.

Second, Post-2022, however, the marginal effect of additional share becomes sharply negative, consistent with a crowding-out of non-IPCC-cited work. The coefficient at $k = +1$ is $\widehat{\beta}_{+1} = -16.1$ (s.e. 7.3), implying that raising the share of IPCC-cited papers from 0 to 1 reduces the average non-cited paper's citations in the first post-report year by roughly sixteen. Put differently, a 10 percentage-point increase in topic share is associated with a loss of about 1.6 citations per paper.

Third, the post-treatment coefficients remain negative and of a similar order of magnitude.

As a robustness check, I re-estimate the event-study using each paper's secondary topic (when available). This mitigates concerns that journal–year matching skews the topic mix of the control group, particularly in early years. By comparing effects across primary and secondary topic assignments—while holding the other fixed—I isolate the marginal impact of treatment along each topic dimension. This provides a quasi-independent test of the main crowding and surplus patterns.T he estimated effects are slightly smaller in magnitude (ranging from +15 citations at $t = -10$ to -11 at $t = -1$), but follow a similar temporal pattern, reinforcing the main findings. The results are also robust to a range of alternative specifications: restricting the sample to Social Sciences, Economics, or the main fields represented in IPCC topics; excluding topics with less than 40 papers; excluding large interdisciplinary journals such as *Nature* and *Science*; and controlling flexibly for both primary and secondary topics, fields and subfields (see Appendix).

7.4 Net aggregate reallocation

To move from per–paper estimates to a field-wide verdict, I aggregate the two event-study effects across topics. For any topic g let s_g be the fraction of its papers cited in AR6. A 100pp rise in that share reduces citations to the remaining papers by $\hat{\beta}_k$ (-20 at k=-1), while each cited paper gains $\hat{\Delta}_k$ (+5 at k=-1). Hence the net change in 2023 is

$$\widehat{\text{Net}} = \sum_{k=-10}^{+2} \left(N^{\text{cited}} \hat{\Delta}_k + \sum_g N_g^{\text{non}} s_g \hat{\beta}_k \right)$$

Over 2012-2024, the total citation net impact is $-274,922$ or -0.74 per paper and per year once normalised by the total observations (year x paper), with a 95% confidence interval of $[-0.962, -0.520]$ (See Appendix G, and Figure 39 for a yearly plot).

IPCC endorsement delivers about five extra citations to each cited paper but, through crowding-out, removes roughly half a citation from the much larger set of uncited papers in the same topics. The mean net effect is therefore negative and statistically indistinguishable from zero, suggesting that the IPCC report reallocates rather than expands scholarly attention.

The standard error of the citations yearly change over the whole papers in IPCC-fields paper (both treated and control) is about 12 citations.[11] The effect I find is then insignificant. The IPCC process is then a pure reallocation of attention and citations

[11] Note that it does include the normal ageing of papers and the growing size of the cohort, it might then be slightly inflated. For cohorts published between in 2012, the standard error of citations received year-on-year is about 10.

7.5 Quality improvement

A quality-improving reallocation would predicts bigger boosts for higher pre-2019 citation percentiles and lower boost for less cited paper pre 2019.

I modify equation (2) for add an interaction with a HighQ variable which indicates whether in 2019 a paper was in the top 20% of cumulative citation of his cohort (same publication year)

$$\text{cit}_{ijt} = \sum_{k\neq -1}\Big[\beta_k\, \mathbb{1}\Big\{\text{event\_time} = k\Big\}_t \times \text{Treat}_i \times \mathbb{1}\Big\{\text{HighQ}\Big\}_i\Big] + \delta\,\text{Cit3}_i + \mu_{ij} + \tau_t + \varepsilon_{ijt}, \tag{5}$$

Table 8 compares the estimates of the equations (2) and (5) on the same panel, and the equation (2) on respectively the High Quality papers pre-IPCC and the rest of the panel (Medium and Low Quality, defined subjectively with percentiles of of citations in 2019).

From the triple interaction equation (5), I can recover the overall average (two-way) from the three-way model,

$$\beta_{\textbf{avg}} = p\beta_{\textbf{HQ-extra}} + (1-p)(\beta_{\textbf{LQ}} + \beta_{\textbf{HQ-extra}}), \tag{6}$$

with $\beta_{\textbf{avg}}$ the coefficient on treat:post in the two-way model, $\beta_{\textbf{HQ-extra}}$ the coefficient on treat:post:HighQ in the three-way and the baseline coefficient $\beta_{\textbf{LQ}}$ from the same model. p is the share of observations where the paper is in the top 20% of its cohort in 2019 (not exactly equal to 20% as older papers have more observations).I compute the standard error of the average coefficient by the delta method.

Quality-weighted inflows of new citations show that any reallocation of attention is towards higher-quality papers.

7.6 Conclusion on Welfare

Taken together, these results indicate that IPCC endorsement operates through reallocation rather than expansion: once a sizeable fraction of a topic's literature is cited by the AR6, residual papers in that topic experience a marked slowdown in annual citations. The crowding-out effect reverses the modest visibility advantage those topics enjoyed beforehand. However, the reallocation of attention is towards higher-quality papers, thus reducing the risk of shift scholarly attention away from un-endorsed but potentially valuable contributions.

8 Conclusion

This paper asks who the IPCC Working Group III (WGIII) cites and what that selection does to scholarly recognition in climate-mitigation research. I assemble the full AR5 (2014), SR15 (2018), and AR6 (2022) WGIII reference lists, harmonize them to bibliometric databases, and match 33,247 cited economics-related papers to 80,000 journal-year controls. Annual citation panels (2000–2024) support an event-study difference-in-differences design; quasi-random 77% chapter-author turnover between AR5 and AR6 provides an instrument for inclusion that parallels judge-reassignment strategies in applied micro.

Three facts emerge. **First, prestige and policy salience diverge**: only 55 of 15,130 AR6 mitigation references (0.36%) appear in the economics "Top 5," while interdisciplinary and policy

Table 8: Difference-in-Differences Estimates of AR6 WGIII Report Impact on Yearly Citations based on pre-event Quality

	All	QxPostxTreat	High Q	Low Q
treat	0.6	−0.5**	2.9+	−1.0***
	(0.4)	(0.1)	(1.6)	(0.1)
cit3	0.3***	0.3***	0.3***	0.3***
	(0.0)	(0.0)	(0.0)	(0.0)
treat × post	3.1***	−0.5*	11.8***	−0.1
	(0.7)	(0.2)	(2.6)	(0.2)
isHighQ		0.8		
		(1.1)		
treat × isHighQ		4.0**		
		(1.5)		
post × isHighQ		10.1***		
		(0.6)		
treat × post × isHighQ		12.6***		
		(2.6)		
Num.Obs.	451 937	451 937	96 840	355 097
R2	0.659	0.662	0.615	0.563
R2 Within	0.498	0.503	0.494	0.351
Std.Errors	by: doi	by: doi	by: doi	by: doi
Journal FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Publication Year FE	✓	✓	✓	✓
Time Since Pub FE	✓	✓	✓	✓

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

Clustered standard errors at the paper (DOI) level.

Columns 1, 3, 4 and 2 represents a different specification.

Columns 1 and 2 are the full panel of papers published 2010-2019,

Columns 3 and 4 are respectively the high and low quality within each cohort.

Table 9: Decomposition of the overall post–2020 boost on quality

Coefficient		Estimate	SE
$\beta_{\mathbf{LQ}}$		−0.336	0.177
$\beta_{\mathbf{HQ\text{-}extra}}$		+12.692	2.925
p		0.218	—
Average:	$\beta_{\mathbf{LQ}} + p\,\beta_{\mathbf{HQ\text{-}extra}}$	2.436	1.357

Note: The large SE on the average boost arises because I are averaging a small-SE parameter (β_{LQ}) with a much noisier one (β_{extra}), and the two are positively correlated in our triple-interaction model.

outlets dominate; the gap narrows only under very broad RePEc definitions of "economics." **Second, IPCC inclusion is an endorsement premium**: DiD estimates show treated papers gain roughly 2 additional citations per year (AR6) and 4 per year (AR5), with effects visible up to two years before formal release as drafts circulate; IV estimates leveraging author turnover imply a 67% increase—about 7 cites/yr off an 11-cite median baseline. **Third, the premium is uneven**: strongest in interdisciplinary journals and for mixed Global North/South teams; negligible for Global South–only papers; economics-only venues see smaller gains.

At the field level, IPCC selection reallocates rather than expands attention. When only a few studies in a topic are cited, they become focal and absorb citations while untreated neighbours lose ground; crowding-out averages ½ citation per uncited paper in fully treated topics, leaving net topic-level citation change indistinguishable from zero. The reallocation is quality-skewed: high pre-period citation quantiles capture most of the gains.

Implications for recognition and academic evaluation. WGIII foregrounds policy-relevant research that often falls outside traditional prestige hierarchies. This paper shows that inclusion in an assessment report acts as a credible signal of quality: treated papers experience a significant and durable citation boost. Recognising uptake in assessment reports (IPCC, IPBES, and analogous bodies), along with substantive contributions to these syntheses (such as authoring, reviewing, and data integration) within tenure and promotion systems that currently overweight journal rank would better align academic incentives with societal impact. The uneven distribution of the citation premium further suggests that fostering interdisciplinary and cross-regional collaboration can enhance the visibility of Global South research; absent deliberate support, endorsement mechanisms risk reinforcing existing structural disparities.

Future work should link IPCC-driven recognition to career outcomes (tenure, grants) and to the diffusion of methods across disciplines, and test whether similar endorsement dynamics operate in emerging science-policy bodies (e.g., IPBES, sectoral climate panels). Doing so would help calibrate evaluation systems to the channels through which research actually reaches policy.

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A Methods

Although structured reference lists are not provided, each chapter of each report contains a reference list at the end. We machine read each report, using regular expressions to isolate each reference and split the reference into its constituent parts. As the references are not provided in a structured format, and the reports differ in format between working groups and assessment reports, there is some potential for missed, or misidentified, references. However, the procedure was adapted for each report, and reference counts for the first chapter were checked against manual counts to validate the approach. The numbers presented should therefore give at least a good indication of the number of references used in each assessment report.

A.1 Data Sources

We focus on references cited in the contribution of the Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (AR6) published in 2022, the contribution of the Working Group III to the 5th Assessment Report of the Intergovernmental Panel on Climate Change (AR5), and the Special Report on the impacts of global warming of 1.5°C.[12]

The three reports, and the previous, are publicly available at https://www.ipcc.ch/reports/.

The reports are available in pdf formats, and there is no references lists available, and the bibliometric database do not provide the references used by the reports.

A.2 Reference extraction from IPCC assessment reports

All bibliographic data for the IPCC Assessment Reports were harvested directly from the official `.pdf` files, in which each chapter concludes with its own list of cited works over multiple pages, two-columns. There is large heterogeneity in citation style due to the evolution of practise and software between the three report, and the variety of materials citing: journal articles, books, institutional reports, working papers, databases, etc. In many cases the prescribed format is imperfectly applied, resulting in missing or superfluous spaces, misplaced punctuation, or inconsistent use of commas, full stops, and colons. References stacked together, missing or wrong indent, etc.

Core workflow. The extraction pipeline is identical across reports, with minor parameter tweaks to accommodate idiosyncrasies of each volume (e.g. year appears in parenthesis in AR5); the architecture and functions remain unchanged throughout. The procedure comprises four main stages:

1. **Page ingestion**. The full `.pdf` is parsed into plain text.

2. **Chapter delimitation**. Regular expressions identify chapter headers and capture the chapter number and title; non-content lines (running heads, footers, side numbers) are discarded.

[12]Technically, the full title of the report is "An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty".

3. **Reference page detection**. Pages containing references are located via keyword heuristics.

4. **Citation reconstruction**. Because entries span two columns and typically wrap across three or four physical lines, the algorithm merges fragments into complete references, correcting for words split across line breaks.

Entry detection. A new reference is flagged when the parser encounters (i) a change in indentation *or* (ii) a token beginning with an upper-case letter or digit, followed by non-punctuation characters, a comma or full stop, a four-digit year in the range 1700–2025 (optionally suffixed by a lower-case letter, e.g. *2002a*), and a terminal colon. To accommodate noisy parsing ot the two columns, the pattern tolerates up to three leading lower-case tokens (e.g. *"and"*) or stray punctuation (dash, ampersand) at the beginning of the citation.

Field segmentation. Once entries are reconstituted, each reference is decomposed into the following components:

- **Digital Object Identifier - DOI.** Identified by the canonical pattern `10.{4{9}/...;` `http(s)://doi.org/` prefixes and trailing full stops are stripped, whitespace is trimmed, empty strings are converted to NA, and the result is lower-cased. If a DOI occurs mid-reference, the line is split immediately after the DOI and before the next capital letter.

- **Authors.** The substring preceding the year is retained, the token *"et al."* is removed, and comma-separated names are collapsed into a semicolon-delimited list.

- **Title.** Taken as the substring between the year and the first full stop (or question mark).

- **Journal or outlet.** Derived from the remainder of the line up to the first comma followed by a digit (volume), the string DOI, or an ISSN.

Hyphenations introduced by line breaks are excised to prevent misclassification. Visual inspection of the machine output led to several dozen manual corrections, primarily to split overly long strings or remove duplicate DOIs.

Identifier assignment. Each occurrence in the raw text is given a row identifier to keep repeated citations across chapters. A unique reference identifier is assigned using the normalised DOI when available, or else an hash of the cleaned text. This guarantees consistent tracking even where metadata are incomplete.

Outputs and coverage. In AR6, the final dataset contains 17,526 reference instances, corresponding to 15,130 distinct references. Each reference is mapped back to every chapter in which it appears, enabling the construction of chapter-level citation metrics used in the empirical analysis.

Although the algorithm delivers a very high share of recoverable and exploitable citations, complete exhaustiveness cannot be guaranteed. Residual gaps stem mainly from extreme formatting anomalies and instances where key metadata (year, DOI) are absent from the source document. All code and intermediate files are released in the replication package.

A.3 Metadata of references

A.3.1 API and metadata prodivers

I access metadata, like journal, authors, doi, citation count, references for some or all of the IPCC references. I'm relying on two databases: OpenAlex and Scopus through their API via R. All API usage complied with the providers' terms of service: request limited to 5 per second, bulk of research done at night in Universal time.

OpenAlex. OpenAlex is a fully open, continuously updated graph of the global research ecosystem, launched in 2022. As of May 2025 it indexes about 258 million research works (journal articles, preprints, book chapters, etc.), 123 million author profiles, and 75 000 journals. Records are sourced primarily from Crossref, PubMed, DOAJ, ROR, ORCID, and institutional repositories, then de-duplicated and linked into a single heterogeneous graph via DOIs, ORCID iDs, and other persistent identifiers. Each work carries rich, open-licensed metadata: titles, abstracts, publication venues, reference lists, field-of-study classifications, full citation links, and open-access status. Coverage is not exhaustive, especially as Elsevier does not provide all of their data. However, we notice no significant difference in data quality among publishers.[13]. OpenAlex citation counts are derived exclusively from open reference data, however, many publishers do not provide historical reference lists, particularly for content published before 2012. As a result, citation counts for 2012 are not provided by OpenAlex. The OpenAlex REST API and supports complex query, allowing for precise data pulling.

Scopus. Scopus, maintained by Elsevier, is a curated abstract-and-citation database that began in 2004 and now contains about 115 million records from 27 000 active serial titles and 300 000 books. The coverage is not exhaustive as the journal selection is performed by an independant board. Tt includes references dating back to 1970 and provides the deepest longitudinal coverage among proprietary citation databases, For this project I accessed Scopus programmatically via the Citation Overview API (one of several REST endpoints exposed to institutional subscribers). This endpoint returns annual citation counts.

A.3.2 Journal matching

Journal titles listed in the IPCC reports are not standardised. Capitalisation varies, the name of the journal may vary abbreviations are applied inconsistently ("Economics", "Econ.", "Econ"), there are some errors arising from the pdf reading, and spurious spaces or punctuation marks are common. These inconsistencies would inflate the count of "rare" journals and understate citations to frequently cited outlets. I therefore perform an intensive normalisation procedure — over twenty-five iterative rounds — to align variant spellings to a single canonical form.

[13]Elsevier does not provide the reference list for each paper for instance, but these informations are still available, although not for all articles, but that seems to be common for all publishers. For Energy Policy, we get an average of 42 secondary references, between 2 and 152, which is aligned with Nature Climate Change with an average of 43 citations (max 137 and min 2

Two external abbreviation catalogues underpin the normalisation: the Web of Science journal-title abbreviation lists[14], and the University of British Columbia's journal-abbreviation database[15] (scraped and cached locally). For every candidate string I query both databases, examining both the full title and all recorded abbreviations. Success of journal identification are propagated to every occurrence of the same reference identifier.

Starting with the raw strings extracted from the pdfs, I apply the following transformations in R, and perform the same look-up for the transformed journal name in both databases.

1. Trim leading, trailing, and repeated whitespace; replace HTML artefacts (`&` → "and").
2. Remove all punctuation
3. Strip initial "The/the", e.g. "The Journal of ..." ↔ "Journal of ...",
4. Expand or contract common ISO abbreviations (e.g. "energy" ↔ "energ"; "sustain" ↔ "sust"; "global" ↔ "glob").
5. Manually created database of abbreviation and full journal name created by targeted web searches.
6. Removing ambiguity, preference was given to spellings using "and" rather than "&" when both appeared in authoritative sources (e.g. "*Renewable and/& Sustainable Energy Reviews*").

For references whose journal remained unidentified, I queried the OpenAlex API with the cited paper's DOI. Retrieved journal titles were then subjected to the same cleaning routine. Where the DOI in the report was corrupted (e.g. extraneous page number in 10.1111/gcb.12561, appearing as10.1111/gcb.12561.855 In this case, the doi is correct in the reference in the pdf, AR6 WG3, chap7, p855, but the page number has been grouped by the doi as it was finishing with a period), the parser truncated the string at the last valid full stop.

The procedure reconciled the vast majority of journal variants; fuzzy string matching, while tested, proved computationally expensive and yielded few additional matches, and was therefore abandoned.

A.3.3 Metadata and citation–count retrieval

Citation count

Missing or unresolvable DOIs. Two recurrent problems arose: i) a DOI is printed in the report but returns no match in OpenAlex, ii) no DOI is printed, yet I have identified a journal name. In both cases I try to remove any spurious suffixes. I then query OpenAlex with a progressively relaxed triplet of search keys—*journal title*, *article title*, *year*. If no hit emerged we dropped the year, then the journal, and finally both, at each stage retaining all candidate matches. Candidate titles were ranked by normalised Levenshtein similarity against the raw title; the highest-scoring entry was provisionally accepted only if similarity exceeded 0.80. All automated matches were subjected to final visual inspection. This routine recovered 51 previously missing DOIs for AR6 and 2,365 for AR5.

[14] `https://images.webofknowledge.com/images/help/WOS/*_abrvjt.html`
[15] `https://journal-abbreviations.library.ubc.ca`

Citation source selection. For every parsed reference of AR6 and SR15 I use OpenAlex (because it is open-source, rate-limited only at generous thresholds) to fetch the yearly citation counts since publication and until 2024. OpenAlex provides usable annual citation counts only from 2012 onwards, consequently for AR5 (2014) we relied on the Scopus "Citation Count Overview" API, which supplies longer historical series. Next step is to fetch the citation count for AR6 using Scopus to check the OpenAlex number, and see whether we get the same results

Coverage achieved. We obtained citation histories for 11,355 unique references in AR6; 4,344 in AR5; and 2,774 in SR15.

Secondary reference harvesting. Using the OpenAlex "referenced_works" endpoint I also downloaded the outbound reference lists of every successfully matched AR6 source. Secondary references were recovered for 10,375 of the 11,355 primary items of AR6, yielding 567,871 cited works (259,598 unique). On average each primary article contributes 55 secondary citations. The secondary set is stored with publication year and journal metadata and is used in Section X to characterise the disciplinary spread of the knowledge base.

A.3.4 Control group construction

To benchmark the citation trajectories of IPCC–cited works against an otherwise comparable set of papers, we constructed a stratified control group. The population of candidate articles is partitioned into cells defined by journal and publication year. This ensures that control papers share the same outlet and vintage as the treated papers, thereby absorbing prestige, level and temporal trends. I did not attempted to match on research field within multidisciplinary outlets such as *Science*, *Nature* or *PNAS*. Instead, the regression specifications incorporate journal fixed effects and dynamic citation controls that absorb field-specific citation propensities and path-dependence.

For every journal–year cell I download up to twelve times the number of IPCC references in that cell (or the full issues published that year by that journal). All treated items are then removed from this pool.

From the remaining articles I drew, without replacement, a random sample equal to ten times the treated count in the same cell (or the maximum available where the desired quota could not be met). Aggregating across cells yields a control panel that is, in expectation, ten times larger than the treated set yet mirrors its joint distribution of journals and publication years.

Annual citation counts for control papers were retrieved from the same sources as the treated set: OpenAlex for AR6 and SR15, and the Scopus Citation Count Overview endpoint for AR5.

For AR6, I have 153,397 candidates for the control group, I select 81,502 of them, and successfully retrieve citation history for 70,332. For AR5, I have 73,238 candidates for the control group, I select 32,781 of them, and successfully retrieve citation history for 32663 For SR15, I have 24,555 candidates for the control group, I select 16,566 of them, and successfully retrieve citation history for 15,229. See appendix F.1, D, and E for the comparison of the composition in years and journals of the control group vs the treated group.

A.3.5 Author identification and harmonisation

The objective is to recover the full list of authors for every cited work and to link these authors to the chapter-level contributor lists printed in the reports.

Parsing authorship strings from references. If the reference line extracted from the PDF contains the token *et al.*, I fetch the the complete author list via OpenAlex. Where all authors are already printed, I split the string on commas and clean each token: misplaced initials are reordered, hyphens in compound forenames are preserved, and stray punctuation or missing full stops are repaired. The outcome is a structured author vector for every reference identifier. Applied to AR6 this yields 35,891 raw author-name strings, which normalise to 27,695 unique individuals across 11,143 references; the analogous figures for AR5 are 19,577 raw names collapsing to 8,728 individuals across 8,779 references.

Extracting the chapter contributor lists. Each IPCC chapter opens with one or two pages enumerating lead authors, contributing authors, review editors, and chapter scientists, etc. I detect these pages, scrape the text blocks, strip the country tags in parentheses, and capture both the chapter number and its title. Because the contributor sections are fully spelled out, they provide a reliable author roste but not in the same form as from references. It yields 561 unique names for AR6, 487 for AR5, and 260 for SR15.

Cross-source name matching. To reconcile the reference-derived authors with the chapter lists I convert every name to two matching keys:

$$\text{key}_1 = \texttt{surname + first initial}, \qquad \text{key}_2 = \texttt{surname + all initials}.$$

For example, "Charles Robert Darwin" becomes `darwin c` and `darwin cr`. Having two keys improves the chance of matching if the form of the name is not exactly the same in the report, in each reference and in OpenAlex. Matches obtained under either scheme are consolidated to the key_1 form, ensuring a consistent identifier across data sources.

Every (reference × chapter × author) triple receives a unique row in the analytical panel. The resulting author–reference incidence matrix contains 115,613 rows for AR6 and 38,448 rows for AR5, providing the backbone for the contributor-level analyses discussed in Section XX.

A.4 Journal quality and disciplinary classification

To assign each outlet both a *disciplinary tag* (Economics vs. Non-economics) and a *quality tier*, I use four independent sources:

1. **CNRS Section 37 list** (2022 edition). The French national research council classifies economics journals into four ordered categories, 1 (top) to 4, used in recruitment and national promotions.
2. **London School of Economics departmental journal lists** (2024 refresh). The LSE publishes ranked outlet lists for its tenure and promotion procedures across Economics, Geography, and allied departments.

3. **SCImago Journal Rank (*SJR*) 2024.** *SJR* provides a citation-weighted percentile for every SCOPUS-indexed title; we map percentiles to quartiles (Q1–Q4).

4. **RePEc journal roster** (downloaded June 2025). RePEc offers the broadest catalogue of economics-related outlets, including multidisciplinary venues (e.g. *Science*, *Nature*, *Nature Climate Change*, *PNAS*).

A journal is flagged as "Economics" if it appears in either the CNRS list or the RePEc roster. Quality tiers are inherit from their CNRS category, the LSE departmental Tier or the SCImago quartile (Q1–Q4) or percentile.

B Matching AR6 and AR5 WGIII Chapters

In this appendix, I detail the computational procedure used to identify thematic correspondences between chapters of the IPCC AR6 and AR5 Working Group III reports using TF–IDF cosine similarity.

B.1 AR5 and AR6 tables of content

Tables 10 and 11 gives the full table of contents of AR6 and AR5 respectively.

Table 10: IPCC AR6 WGIII table of content

Chapter	
1	Introduction and Framing
2	Emissions Trends and Drivers
3	Mitigation Pathways Compatible with Long-term Goals
4	Mitigation and Development Pathways in the Near to Mid-term
5	Demand, Services and Social Aspects of Mitigation
6	Energy Systems
7	Agriculture, Forestry and Other Land Uses (AFOLU)
8	Urban Systems and Other Settlements
9	Buildings
10	Transport
11	Industry
12	Cross-sectoral Perspectives
13	National and Sub-national Policies and Institutions
14	International Cooperation
15	Investment and Finance
16	Innovation, Technology Development and Transfer
17	Accelerating the Transition in the Context of Sustainable Development
Annex I	Glossary
Annex II	Definitions, Units and Conventions
Annex III	Scenarios and Modelling Methods

Table 11: IPCC AR5 WGIII table of content

Chapter	
1	Introductory Chapter
2	Integrated Risk and Uncertainty Assessment of Climate Change Response Policies
3	Social, Economic, and Ethical Concepts and Methods
4	Sustainable Development and Equity
5	Drivers, Trends and Mitigation
6	Assessing Transformation Pathways
7	Energy Systems
8	Transport
9	Buildings
10	Industry
11	Agriculture, Forestry and Other Land Use (AFOLU)
12	Human Settlements, Infrastructure, and Spatial Planning
13	International Cooperation: Agreements & Instruments
14	Regional Development and Cooperation
15	National and Sub-national Policies and Institutions
16	Cross-cutting Investment and Finance Issues
Annex I	Glossary, Acronyms and Chemical Symbols
Annex II	Metrics & Methodology
Annex III	Technology-specific Cost and Performance Parameters

B.2 Methods

PDF Parsing and Chapter Text Extraction Each PDF (AR6 and AR5) is parsed using the `pdftools` package in `R`. Text and word-level data are extracted from all pages using `pdf_text()` and `pdf_data()`, respectively. I identify chapter boundaries using a custom function `find_author_pages()`, which flags pages containing chapter-author headings. For each page, I assign a type (`"chapter_start"`, `"body"`, or `"references_start"`) based on the presence of chapter headings or the word "References" using regular expressions.

For body pages, the content is reconstructed in reading order by clustering and sorting word tokens by their (x, y) coordinates, and then cleaning the resulting text (non-ASCII characters removed, whitespace squished). If the current page reintroduces the chapter heading, it is removed using a regex anchored to the detected chapter number and name. Each page is annotated with the current chapter number and heading based on the last detected `chapter_start`.

To ensure consistency, chapter headings are disambiguated using `fix_chapter_names()`, which selects the most frequent heading string for each chapter number across all pages.

Constructing Chapter-Level Corpus The body pages are collapsed by chapter using `collapse_by_chapter()`, which groups rows by `(chapter_num, chapter_name)` and concatenates their text fields. Each document is assigned a unique ID (e.g., `AR6_3`) and a label (e.g., "3: Mitigation Pathways").

The full corpus is formed by combining AR6 and AR5 chapter-level documents. A `quanteda` corpus is constructed with these texts and their labels.

Tokenisation and TF–IDF Construction I preprocess the corpus using `quanteda`'s `tokens()` pipeline, which lowercases text, removes punctuation, numbers, and English stopwords, and applies stemming (Snowball algorithm, which reduces words to their root forms by stripping common suffixes). I build a document-feature matrix (DFM) and apply TF–IDF weighting using `dfm_tfidf()`.

Cosine Similarity Computation The TF–IDF matrix is split into AR6 and AR5 subsets, denoted `dfm_ar6` and `dfm_ar5`. I compute cosine similarity between all AR6 and AR5 chapters. Each document vector is ℓ_2-normalised row-wise. The similarity matrix is then computed as:

$$\mathrm{sim}(A, B) = A^*(B^*)^\top,$$

where A^* and B^* are the row-normalised matrices for AR6 and AR5, respectively.

Best-Match Selection For each AR6 chapter, I extract the column (AR5 chapter) with the maximum cosine similarity score from the AR6 × AR5 matrix. I collect and store the triplet:

$$(\text{AR6 chapter label}, \ \text{AR5 best match}, \ \text{cosine similarity}).$$

This yields a one-to-one mapping from each AR6 chapter to its closest AR5 thematic counterpart under the TF–IDF–cosine metric.

Validation and Bias Considerations I construct the TF–IDF feature space jointly over all AR5 and AR6 documents, but I explicitly exclude AR6–AR6 similarities when determining best AR5 matches. This avoids within-document bias: AR6 chapters are more similar to each other (stylistically and terminologically) than to AR5 chapters, and would otherwise dominate the cosine rankings.

Reproducibility The full pipeline is implemented in `R` using the following packages: `pdftools`, `quanteda`, `stringr`, `dplyr`, and `pheatmap`. All intermediate outputs (collapsed chapter texts, TF–IDF matrices, cosine similarity matrices) are cached and can be regenerated from the raw PDFs using the provided scripts.

B.3 Results

To identify the closest thematic match in AR5 for each chapter in the AR6 Working Group III report, I computed pairwise cosine similarities between chapter-level TF–IDF vectors. The full text of each chapter was extracted from the official PDF, pre-processed by tokenising, removing stopwords, lowercasing, and stemming, and transformed into a TF–IDF matrix jointly across AR5 and AR6 documents. Cosine similarity scores were calculated for each AR6 chapter against every AR5 chapter.

Figure 16 visualises the full matrix of AR6 (rows) × AR5 (columns) similarity scores. Tiles are shaded by absolute cosine similarity; white-framed values mark the best AR5 match for each AR6 chapter. White text is used for readability only on higher-similarity tiles. Axis labels follow the official chapter numbering, with abbreviated labels to preserve legibility.

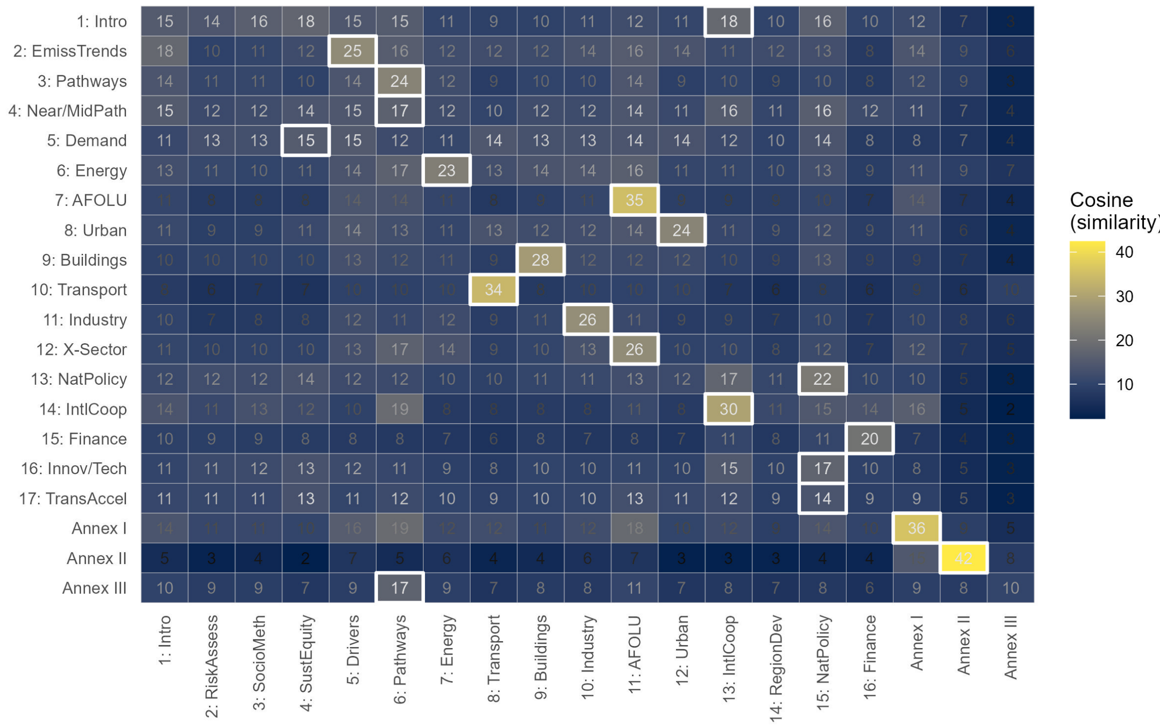


Figure 16: Cosine similarity between AR6 and AR5 chapters (TF–IDF based). For each AR6 chapter (row), the AR5 chapter (column) with the highest similarity is outlined in white.

All matches were checked against chapter titles and key subsections to ensure genuine thematic overlap.

Some matches are rather obvious as there is direct equivalent of AR5 to AR6. These chapters are continuations of sectoral mitigation content and exhibit substantial textual overlap: **AR6 Ch 6 → AR5 Ch 7 (Energy Systems)**, **Ch 9 → Ch 9 (Buildings)**, **Ch 10 → Ch 8 (Transport)**, and **Ch 11 → Ch 10 (Industry)**. **AR6 Ch 13 → AR5 Ch 15 (National Policies)** and **Ch 14 → Ch 13 (International Cooperation)** also display near-verbatim retention of institutional vocabulary, despite minor updates (e.g. post-Paris Agreement mechanisms).

More nuanced cases arise where AR6 introduces new structural emphases or combines previously separate topics.

- **AR6 Ch 5 (Demand, Services and Social Aspects)** finds no perfect match in AR5. Its closest textual counterpart is Ch 4 (Sustainability and Equity), which contained sections on demand-side measures and behavioural drivers, but AR6 introduces a genuinely novel textual emphasis on lifestyles and service provisioning.

- **AR6 Ch 12 (Cross-sectoral Perspectives)** is a synthetic chapter that blends life-cycle, equity, and interlinkage themes. The closest match appears to the AR6 Ch11 AFOLU.
- **AR6 Ch 16 (Innovation, Technology and Transfer)** is another structurally new addition
- **AR6 Ch 17 (Transition and Sustainable Development)** scores lowest among all mappings and has no great match.

B.4 Alternative: Mapping on common authors

As an alternative to content-based analysis, one could use author overlap to match chapters across reports. However, with a 77% turnover in authors between AR5 and AR6, this approach is potentially noisy. Figure 17 shows that while author similarity performs reasonably well for some chapters, it often results in ambiguous matches. In contrast, content similarity offers clearer one-to-one mappings between chapters, making it a more reliable method for tracking continuity across assessment cycles.

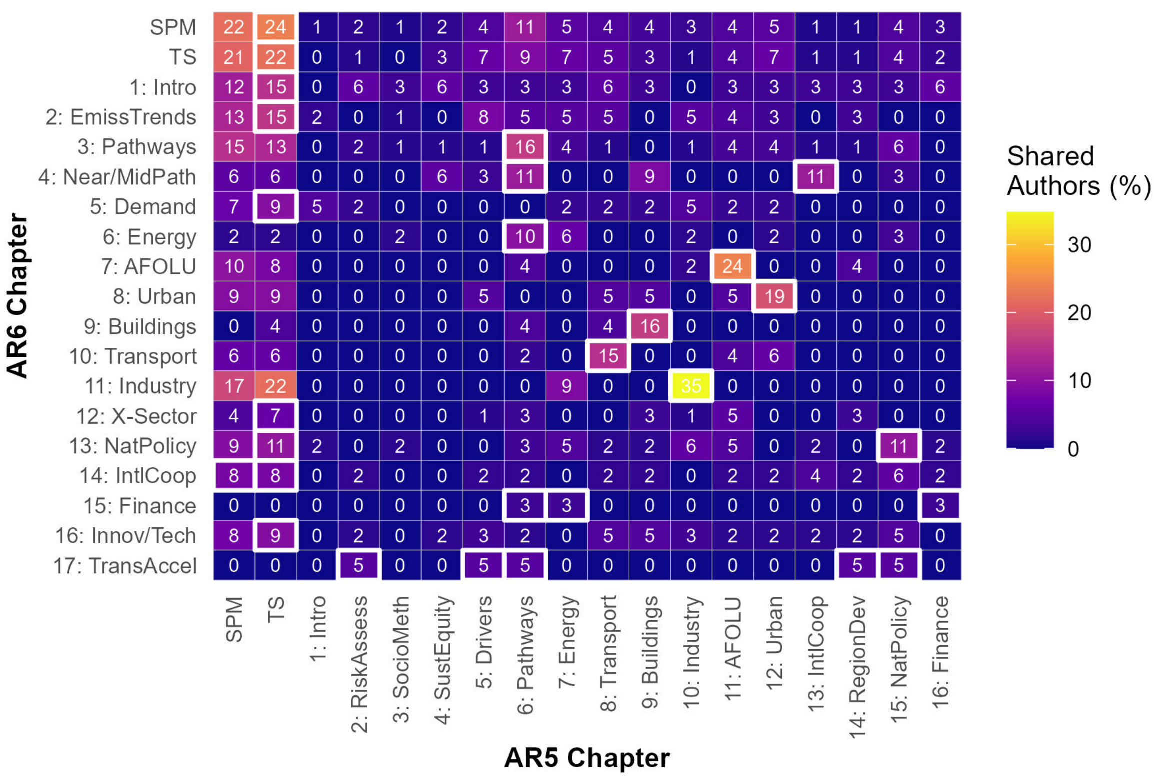


Figure 17: Share of AR6 authors common to AR5 chapter. For each AR6 chapter (row), the AR5 chapter (column) with the highest similarity is outlined in white.

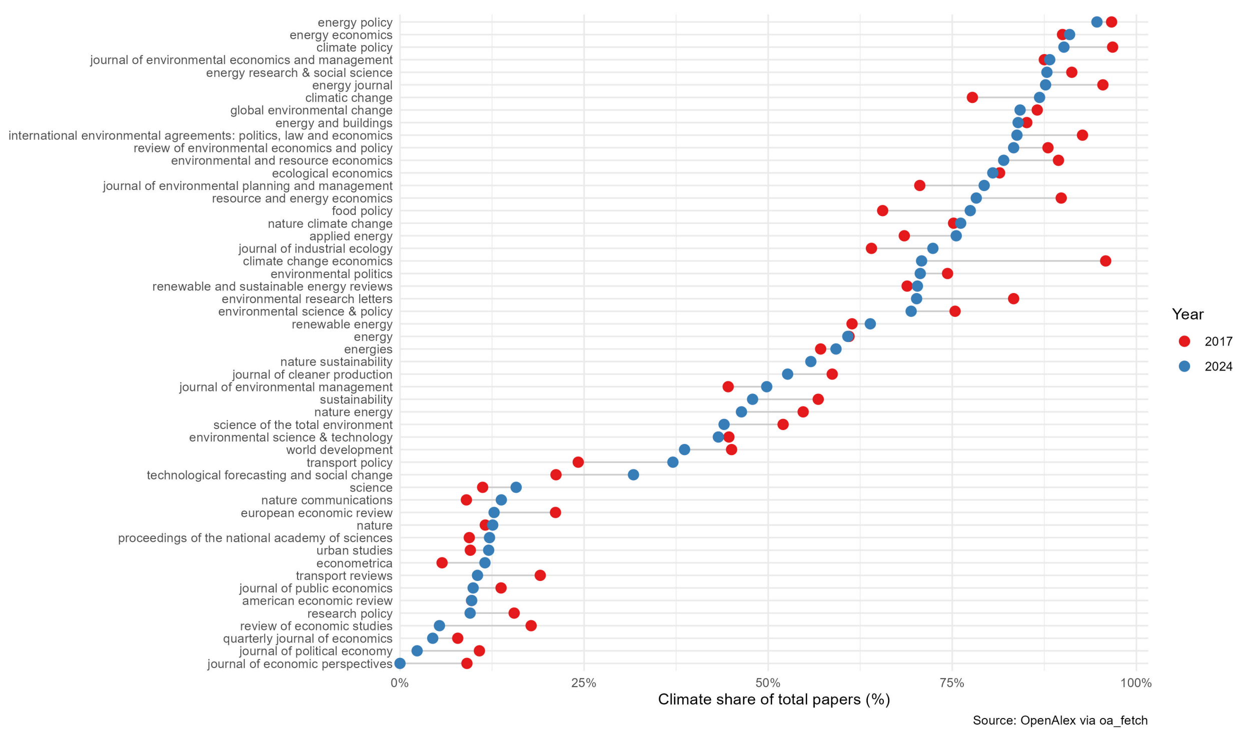
C Robustness checks

C.1 Share of climate related articles

The share of climate-related papers has not changed dramatically between 2017 and 2024 for the top journals referenced by the IPCC (Figure 18). I define a paper as ”climate-related” if at least one of its assigned OpenAlex topics contains any of the following keywords: ”Energy”, ”Environment”, ”Climate”, ”Emissions”, ”Sustainability”, ”Electric”, ”Biofuel”, ”Agricultural”, ”Agriculture”, ”Natural Resources”, ”CO_2”, or ”Carbon”. I download every papers published by the top 30 journals cited in the IPCC, plus the top 25 economics journals cited by the IPCC. The number of articles is up to 10,000 for Sustainability and Nature Communications and 8,500 for Science of the Total Environment.

As the IPCC WGIII is focused on Climate Change Mitigation, I do not include keywords such as Biodiversity, or damages (e.g. flood, heatwaves, etc) as they pertain respectively to the IPBES and the IPCC WGII.

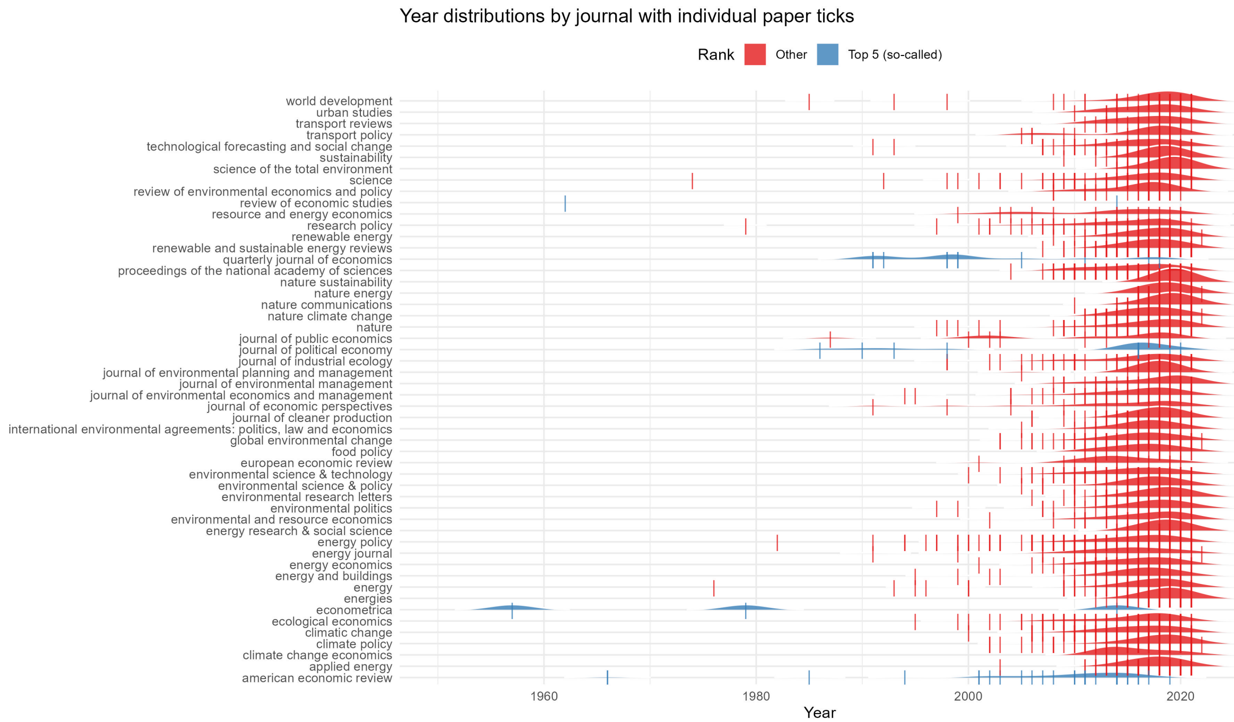
Figure 18: Share of Climate-Related Papers by Journal



The share of climate related articles of top interdisciplinary journals like Nature (12.6%), Science (15.7%), PNAS (12.1%) is somewhat larger to the share in top economics journal: AER (9.7%), QJE (4.4%), JPE (2.3%), Restud (5.3%), ECMA (11.5%). Specialist journal have rates above 80%: Energy Policy (95%), Energy Economics (91%), JEEM (88%), Ecological Economics (80%).

For the papers cited in the IPCC AR6 WGIII, the top economics journal draw papers from a larger period than environmnent-focused outlets (Figure 19).

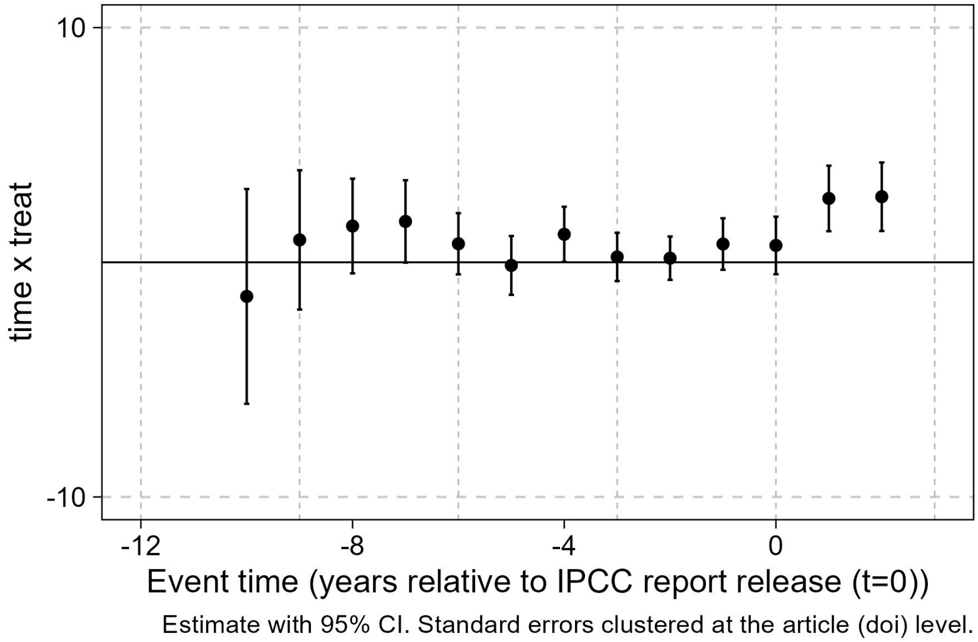
Figure 19: Year distributions by journal



C.2 Excluding self-cited references

To rule out the impact of IPCC-reference on citation boost as a by-product of author self-citation in the IPCC, we exclude all within-chapter self-cites (meaning the reference is excluding if it is cited in one chapter where one of its authors has a role, even if cited in other chapters independently). The AR6 citation boost falls only marginally

Figure 20: Dynamic impact of AR6 citation without within-chapter self-citations



C.3 Controlling for self-cited references

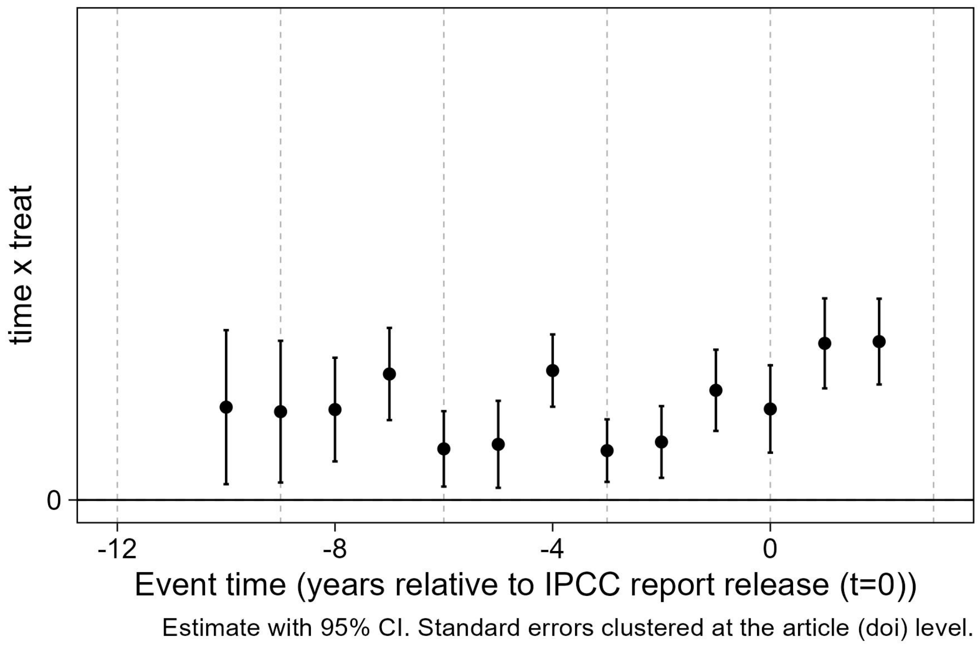
To rule out the impact of IPCC-reference on citation boost as a by-product of author self-citation in the IPCC, we control for all within-chapter self-cites (meaning the dummy is 1if it is cited in one chapter where one of its authors has a role, even if cited in other chapters independantly). The AR6 citation boost is unchanged. See Figure 21 and Table 13.

Table 12: Difference-in-Differences Estimates of AR6 WGIII Report Impact on Yearly Citations - without within-chapter self-citations

	(1)	(2)	(3)	(4)	(5)
treat	0.4	0.3	0.6	107.6*	2.2*
	(0.4)	(0.4)	(0.4)	(47.9)	(0.9)
cit3	0.3***	0.3***	0.3***	−0.2	
	(0.0)	(0.0)	(0.0)	(0.1)	
treat × post	1.4*	1.5*	1.5*	2.6***	1.5*
	(0.6)	(0.6)	(0.6)	(0.7)	(0.7)
post		0.5	0.1	−86.0	−2.8
		(2 400 252.4)	(7 401 353.7)	(60.1)	(8 747 187.1)
Num.Obs.	553 662	553 662	553 662	553 662	560 642
R2	0.563	0.572	0.579	0.775	0.252
R2 Within	0.425	0.432	0.438	0.000	0.000
Std.Errors	by: doi	by: doi	by: doi	by: doi	by: doi
Journal FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Publication Year FE		✓		✓	✓
Time Since Pub FE		✓	✓	✓	✓
DOI FE				✓	

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001
Clustered standard errors at the paper (DOI) level.
Each column represents a different fixed effects specification.

Figure 21: Dynamic impact of AR6 citation with control of within-chapter self-citations



D AR5

Description of the sample for AR5, characteritics of the treated and control group in terms of journal (Table 15) and publication year (Table 14).

Table 13: Difference-in-Differences Estimates of AR6 WGIII Report Impact on Yearly Citations - controling for within-chapter self-citations

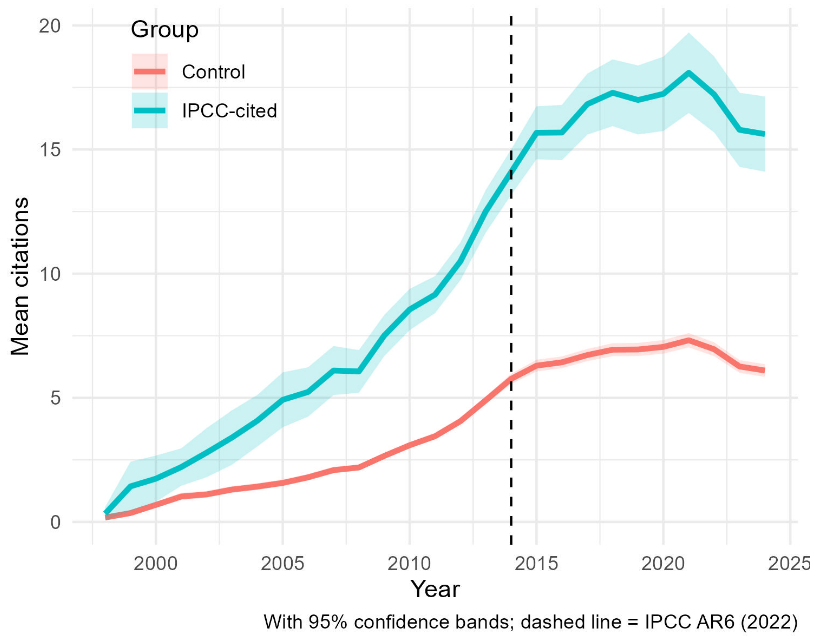
	(1)
treat	5.8***
	(1.4)
cit3	0.0***
	(0.0)
is_self_cit	−3.7
	(4.7)
treat × post	9.0***
	(1.7)
post × is_self_cit	22.4+
	(12.2)
Num.Obs.	202 958
R2	0.573
R2 Within	0.407
Std.Errors	by: doi
Journal FE	✓
Year FE	✓
Publication Year FE	✓
Time Since Pub FE	✓
DOI FE	

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Clustered standard errors at the paper (DOI) level.
Each column represents a different fixed effects specification.

Table 14: Number of articles by treatment status and publication year (AR6 WGIII)

Publication Year	Control	Treatment	Control/Treatment Ratio
1998	207	26	7.96
1999	290	32	9.06
2000	460	58	7.93
2001	367	44	8.34
2002	388	52	7.46
2003	550	65	8.46
2004	638	78	8.18
2005	803	88	9.12
2006	1400	175	8.00
2007	1950	225	8.67
2008	2163	298	7.26
2009	3431	420	8.17
2010	4406	511	8.62
2011	5192	622	8.35
2012	4979	604	8.24
2013	3387	389	8.71

Figure 22: Average yearly citations: AR5 references vs. control papers



Notes: Shaded bands show 95% confidence intervals. Vertical dashed line marks the release of AR5 (2014).

Table 15: Number of articles by treatment status and journal (AR6 WGIII)

Journal	Control	Treatment	Control/Treatment Ratio
energy policy	4149	433	9.58
climatic change	1745	196	8.90
ecological economics	994	96	10.35
energy economics	869	122	7.12
science	791	85	9.31
proceedings of the national academy of sciences	675	76	8.88
renewable and sustainable energy reviews	630	64	9.84
climate policy	578	129	4.48
environmental research letters	558	62	9.00
global environmental change	550	54	10.19
international journal of greenhouse gas control	533	55	9.69
nature climate change	456	46	9.91
journal of cleaner production	440	44	10.00
nature	410	43	9.53
journal of environmental economics and management	399	44	9.07
environmental and resource economics	379	38	9.97
biomass and bioenergy	370	36	10.28
american economic review	340	34	10.00
journal of industrial ecology	339	43	7.88
energy and buildings	319	32	9.97
mitigation and adaptation strategies for global change	309	41	7.54
energy	300	46	6.52
current opinion in environmental sustainability	283	32	8.84
applied energy	240	23	10.43
building and environment	210	21	10.00

Table 16: Difference-in-Differences Estimates of AR5 WGIII Report Impact on Yearly Citations

	(1)	(2)	(3)	(4)	(5)
treat	1.1***	0.8**	0.8**	23.9	6.4***
	(0.2)	(0.3)	(0.3)	(251.6)	(0.3)
cit3	0.3***	0.3***	0.3***	0.4	
	(0.0)	(0.0)	(0.0)	(7.4)	
treat × post	4.8***	4.8***	4.9***	6.1***	4.2***
	(0.2)	(0.2)	(0.2)	(0.3)	(0.3)
post		−6.4	−7.8	34.2	2.0
		(1 421 325.0)	(1 053 911.6)	(167.6)	(1 326 582.9)
Num.Obs.	541 401	541 401	541 401	541 401	541 467
R2	0.453	0.466	0.475	0.779	0.207
R2 Within	0.385	0.399	0.404	0.034	0.099
Std.Errors	by: doi	by: doi	by: doi	by: doi	by: doi
Journal FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Publication Year FE		✓		✓	✓
Time Since Pub FE		✓	✓	✓	✓
DOI FE				✓	

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

Clustered standard errors at the paper (DOI) level.

Each column represents a different fixed effects specification.

Table 17: Difference-in-Differences Estimates of AR5 WGIII Report Impact on log Yearly Citations

	(1)	(2)	(3)	(4)	(5)
treat	0.260***	0.123***	0.118***	−6.791	0.765***
	(0.012)	(0.011)	(0.010)	(60.458)	(0.018)
log1p(cit3)	0.507***	0.641***	0.642***	1.036	
	(0.003)	(0.003)	(0.003)	(4.956)	
treat × post	0.181***	0.192***	0.197***	0.268***	0.168***
	(0.014)	(0.013)	(0.013)	(0.013)	(0.015)
post		1.365	1.236	10.362	1.074
		(112 853.496)	(80 887.096)	(20.923)	(117 272.273)
Num.Obs.	541 401	541 401	541 401	541 401	541 467
R2	0.461	0.522	0.562	0.765	0.257
R2 Within	0.367	0.438	0.460	0.006	0.084
Std.Errors	by: doi	by: doi	by: doi	by: doi	by: doi
Journal FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Publication Year FE		✓		✓	✓
Time Since Pub FE		✓	✓	✓	✓
DOI FE				✓	

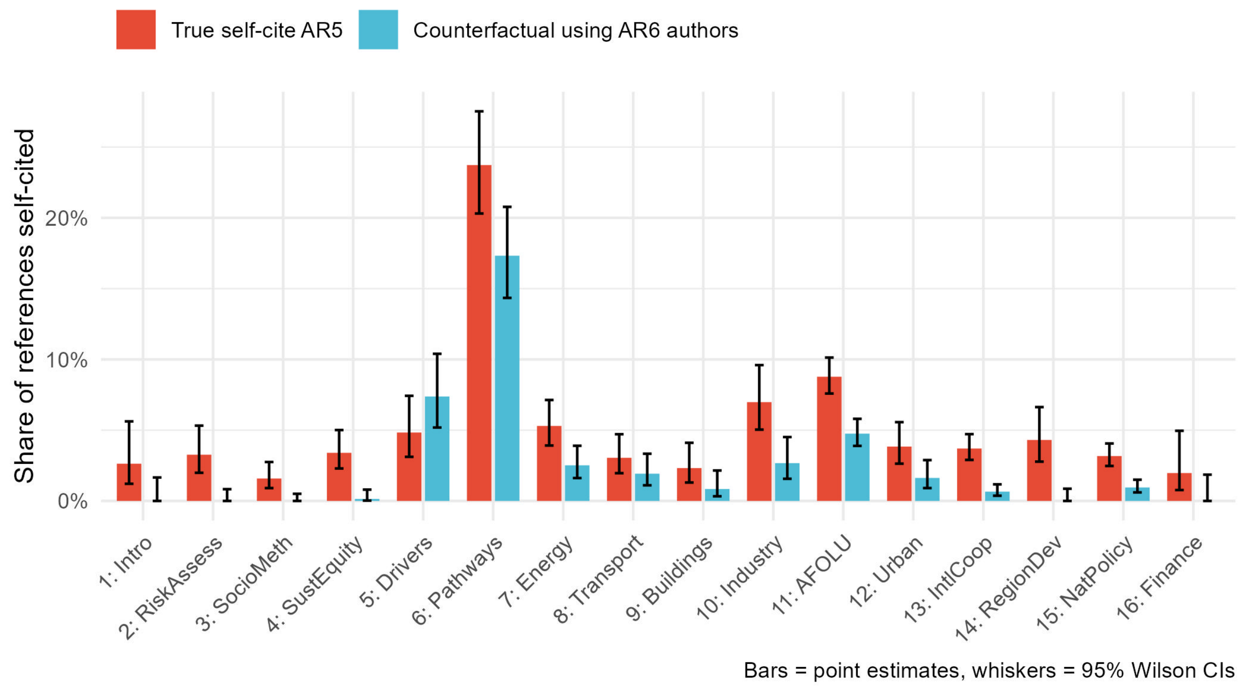
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Clustered standard errors at the paper (DOI) level.

Each column represents a different fixed effects specification.

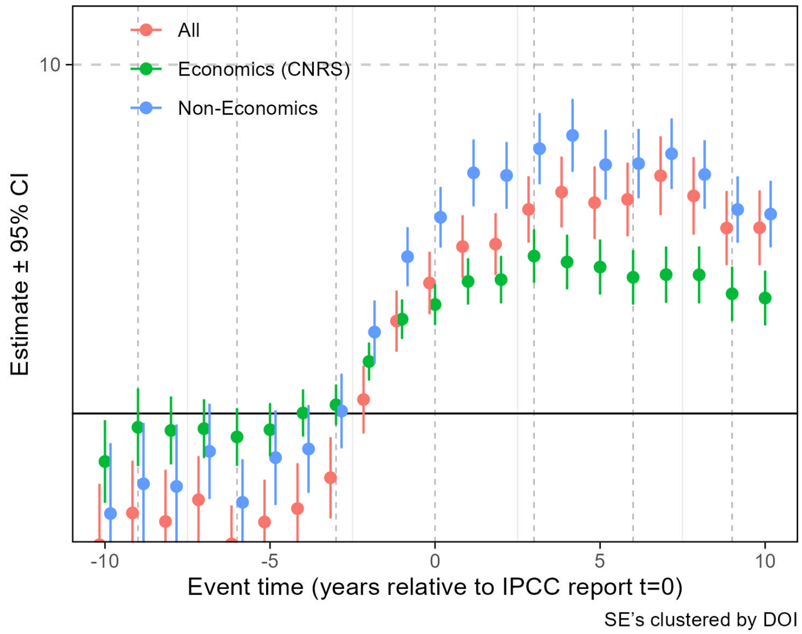
D.1 Self-citation in AR5 chapters

Figure 23: Chapter-level self-citation shares in AR5 and in equivalent AR6 chapters



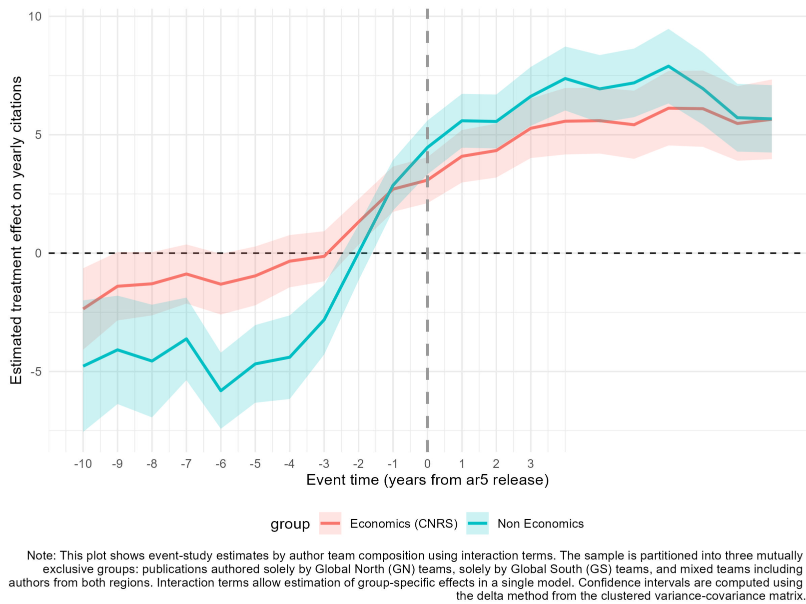
Focus on econ journal Figure 24, makes sense to have a lower effects, Econ is know to have lower citations anyway (might be bigger in relative actually).

Figure 24: Average yearly citations: AR5 references vs. control papers in Economics journal



Notes: Shaded bands show 95% confidence intervals. Vertical dashed line marks the release of AR5 (2014). Light jitter in time (x-axis) to better visualisation of the confidence intervals. We use the CNRS Economics Journals ranking, as it excludes big interdisciplinary journals like Nature, Nature Climate Change, etc.

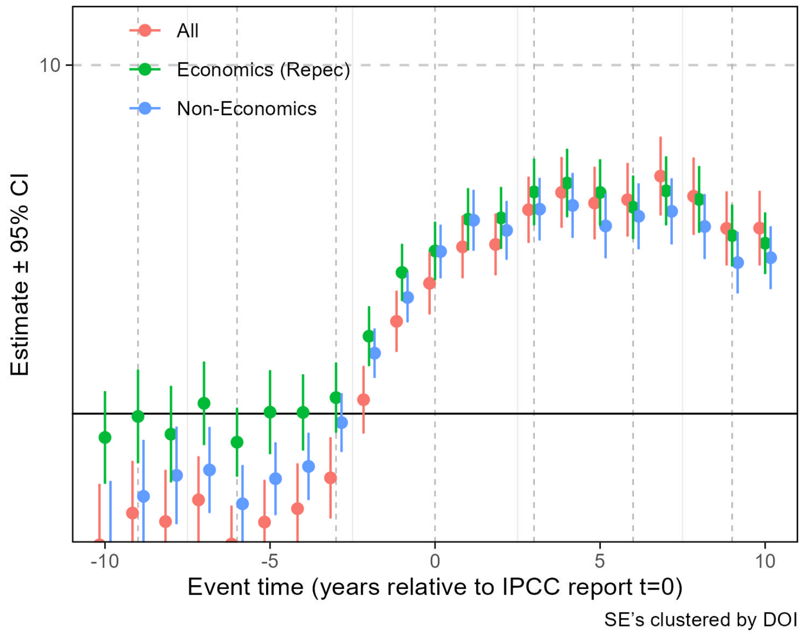
Figure 25: Average yearly citations: AR5 references vs. control papers in Economics journal in Triple Difference model



Notes: Shaded bands show 95% confidence intervals. Vertical dashed line marks the release of AR5 (2014). Light jitter in time (x-axis) to better visualisation of the confidence intervals. I use the CNRS Economics Journals ranking, as it excludes big interdisciplinary journals like Nature, Nature Climate Change, etc.

When using repec (looser def of econ, including PNAS, but not Science or Nature, etc), we don't see a difference.

Figure 26: Average yearly citations: AR5 references vs. control papers in Economics journal using REPEC classification



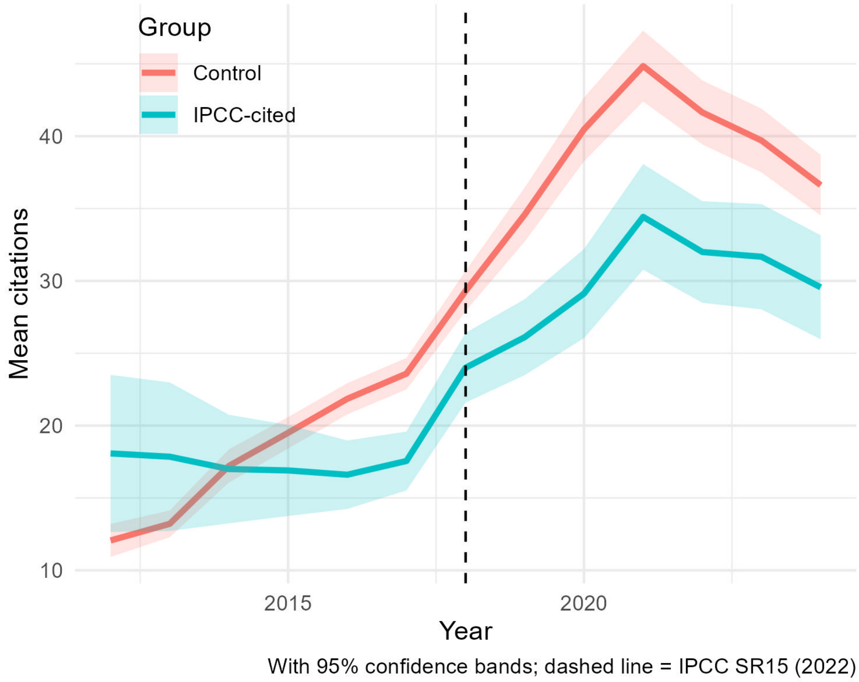
Notes: Shaded bands show 95% confidence intervals. Vertical dashed line marks the release of AR5 (2014). Light jitter in time (x-axis) to better visualisation of the confidence intervals. We use the CNRS Economics Journals ranking, as it excludes big interdisciplinary journals like Nature, Nature Climate Change, etc.

E SR15 Citation Effects

In this appendix, we replicate our main analysis around the Special Report on Global Warming of 1.5 °C (SR15, released in 2018) to verify whether the citation boost observed for the AR5 and AR6 reports generalise to every IPCC publication.

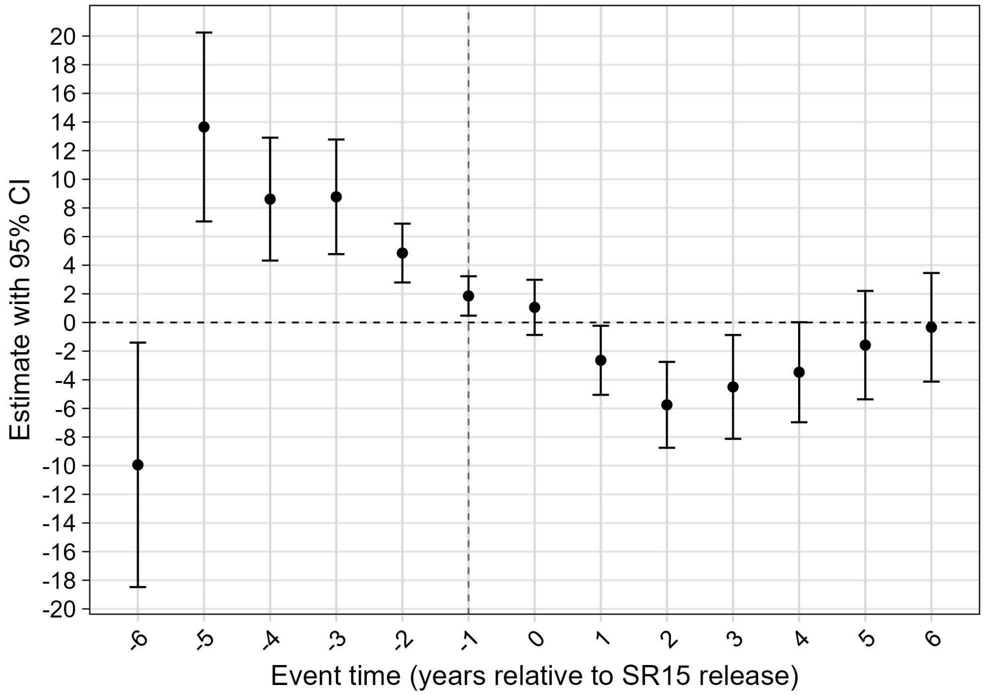
Figure 27 plots the mean annual citations for SR15–cited papers versus their matched controls; there is no discernible divergence post-2018. Table 18, shows identical null results. The event–study in Figure 28 likewise shows coefficients statistically indistinguishable from zero in all years following SR15's release. To ensure that AR6 citations do not contaminate this exercise, we limit the control and treated groups to papers not involved in the AR6. We further limit the sample to economics journals only, still seeing no impact of the SR15 publication on citations.

Figure 27: Average yearly citations: SR15 references vs. control papers



Notes: Shaded bands show 95% confidence intervals. Vertical dashed line marks the release of SR15 (2018).

Figure 28: Event–study: SR15 citation impact on yearly citations



Notes: Coefficients from Eq. (2) with 95 % CIs; SEs clustered by DOI; $k = -1$ omitted.

Potential explanations for the null SR15 effect.

- **Scope and novelty.** SR15 is more specialised (limiting warming to 1.5°C) and carries less broad methodological content than the comprehensive Assessment Reports, hence conferring smaller "shock" value to the underlying literature.
- **Audience composition.** SR15's primary uptake was among policymakers, reducing spill-over into journal citations.

These results show that the citation premium we document is specific to the large Assessment Reports (AR5 and AR6) and does not arise mechanically for every IPCC product.

Table 18: Difference-in-Differences Estimates of SR15 WGIII Report Impact on Yearly Citations

	(1)	(2)	(3)	(4)	(5)
treat	3.5***	3.7***	3.8***	642.3	3.4*
	(0.9)	(0.8)	(0.8)	(3164.3)	(1.4)
cit3	0.3***	0.3***	0.3***	0.0	
	(0.0)	(0.0)	(0.0)	(1.2)	
treat × post	−4.8***	−5.2***	−5.1***	−3.9***	−4.0**
	(1.2)	(1.1)	(1.1)	(1.1)	(1.2)
post			11.0	−57.5	3.7
			(9 555 246.6)	(342.2)	(9 590 187.8)
Num.Obs.	117 595	117 595	117 595	117 595	127 832
R2	0.536	0.549	0.560	0.820	0.391
R2 Within	0.261	0.277	0.283	0.000	0.000
Std.Errors	by: doi	by: doi	by: doi	by: doi	by: doi
Journal FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Publication Year FE		✓		✓	✓
Time Since Pub FE		✓	✓	✓	✓
DOI FE				✓	

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

Clustered standard errors at the paper (DOI) level.

Each column represents a different fixed effects specification.

Table 19: Number of articles by treatment status and publication year (AR6 WGIII)

Publication Year	Control	Treatment	Control/Treatment Ratio
2010	1191	127	9.38
2011	1359	158	8.60
2012	1957	199	9.83
2013	2828	283	9.99
2014	4135	381	10.85
2015	5233	504	10.38
2016	7543	725	10.40
2017	9174	880	10.43
2018	12193	1106	11.02
2019	12418	1121	11.08
2020	11075	1028	10.77
2021	6587	530	12.43

Table 20: Number of articles by treatment status and journal (AR6 WGIII)

Journal	Control	Treatment	Control/Treatment Ratio
energy policy	4557	391	11.65
journal of cleaner production	3189	257	12.41
environmental research letters	2740	298	9.19
renewable and sustainable energy reviews	2620	2	1310.00
applied energy	2050	177	11.58
nature climate change	2044	249	8.21
climatic change	1725	161	10.71
sustainability	1630	129	12.64
energy research & social science	1617	47	34.40
energy	1589	134	11.86
proceedings of the national academy of sciences	1309	47	27.85
energy economics	1260	103	12.23
ecological economics	1203	94	12.80
nature communications	1190	100	11.90
global environmental change	1148	37	31.03
environmental science & technology	1060	81	13.09
energy and buildings	1000	91	10.99
nature	980	89	11.01
science	970	87	11.15
energies	950	84	11.31
nature energy	840	89	9.44
science of the total environment	790	66	11.97
technological forecasting and social change	767	32	23.97
environmental science & policy	752	63	11.94
renewable energy	700	59	11.86

F AR6 supplementary facts

F.1 Description of the sample

F.2 Log citations

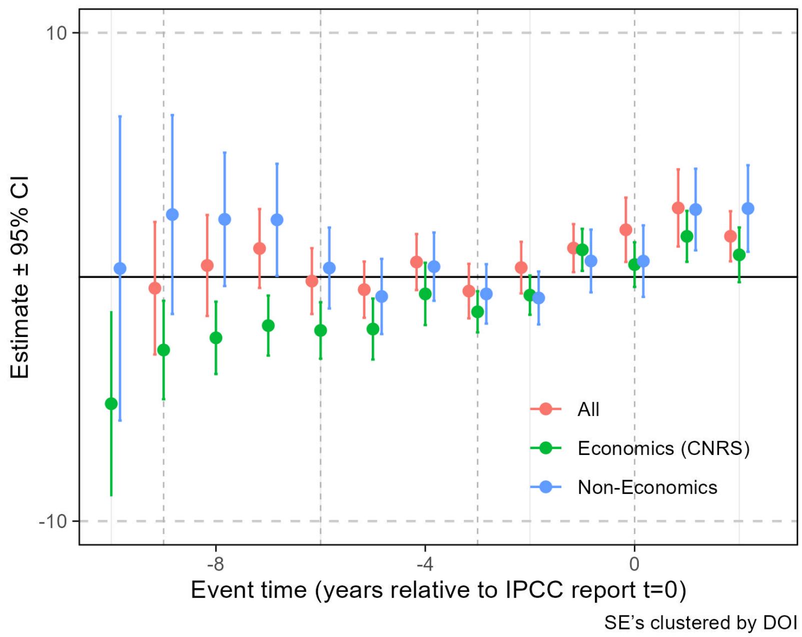
Table 21: Difference-in-Differences Estimates of AR6 WGIII Report Impact on log Yearly Citations

	(1)	(2)	(3)	(4)	(5)
treat	0.018*	−0.014**	0.005	−4.223	0.168***
	(0.007)	(0.005)	(0.005)	(3.060)	(0.014)
log1p(cit3)	0.617***	0.748***		−0.611***	
	(0.003)	(0.002)		(0.160)	
treat × post	−0.021*	−0.018*	−0.032***	−0.016*	−0.039***
	(0.009)	(0.008)	(0.006)	(0.006)	(0.009)
post		2.014	0.243	−7.295***	0.015
		(26 980.086)	(85 404.897)	(1.104)	(130 236.408)
log(cit3)			0.703***		
			(0.002)		
Num.Obs.	561 873	561 873	561 873	561 873	568 924
R2	0.652	0.706	0.782	0.858	0.541
R2 Within	0.357	0.442	0.523	0.000	0.003

F.3 Econ

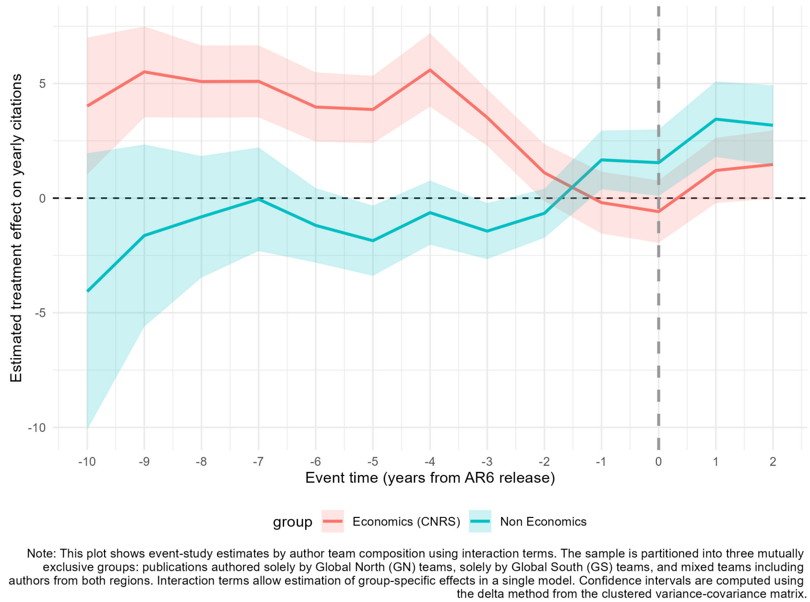
Focus on econ journal Figure 29, using the CNRS one, no more impact. But still one when using REPEC, it might be due to Nature Climate Change then.

Figure 29: Average yearly citations: AR6 references vs. control papers in Economics journal



Notes: Shaded bands show 95% confidence intervals. Vertical dashed line marks the release of AR6 (2014). Light jitter in time (x-axis) to better visualisation of the confidence intervals. We use the CNRS Economics Journals ranking, as it excludes big interdisciplinary journals like Nature, Nature Climate Change, etc.

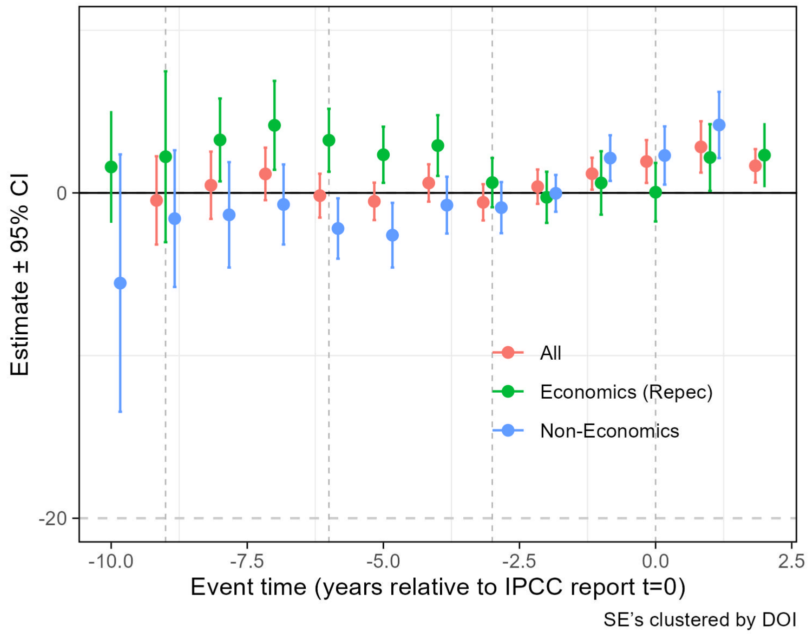
Figure 30: Average yearly citations: AR6 references vs. control papers in Economics journal in Triple Difference model



Notes: Shaded bands show 95% confidence intervals. Vertical dashed line marks the release of AR5 (2014). Light jitter in time (x-axis) to better visualisation of the confidence intervals. I use the CNRS Economics Journals ranking, as it excludes big interdisciplinary journals like Nature, Nature Climate Change, etc.

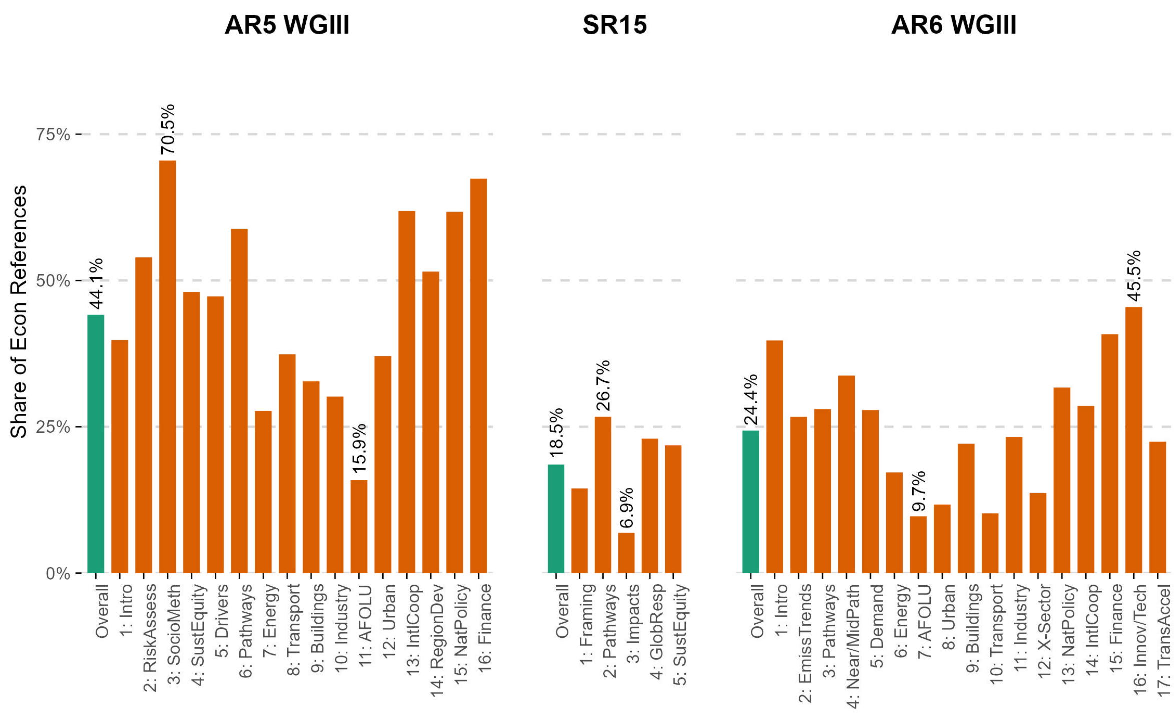
When using repec (looser def of econ, including PNAS, but not Science or Nature, etc), we don't see a difference.

Figure 31: Average yearly citations: AR6 references vs. control papers in Economics journal using REPEC classification



Notes: Shaded bands show 95% confidence intervals. Vertical dashed line marks the release of AR6 (202). Light jitter in time (x-axis) to better visualisation of the confidence intervals. We use the REPEC Economics Journals definition.

Figure 32: Economic-Journal References in IPCC Reports (REPEC)



Notes: I use the REPEC Economics journal ranking to classify Economics references. For a narrower definition of economomics see Figure 40 same graph using the REPEC classification of journal.

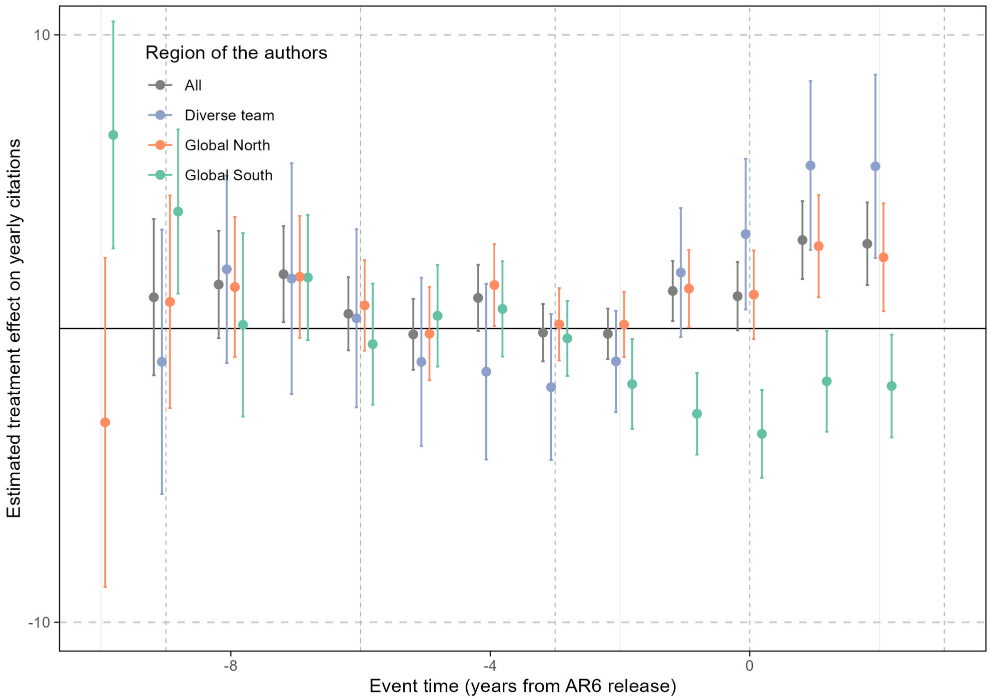
F.4 Global North vs South

To complete Figure 6, I restrict equation (2) to Global North-only papers, Global South only, and diverse teams of authors for treated and control group (Table 22). The Event study plot, Figure 33, shows that the results are similar to Figure 6, with no effect on global south only citation count.

Table 22: Distribution of papers by authors' region of origin

Authors' region	Treatment	Papers	Share
Global North	Treated group	4621	65.9%
Global South	Treated group	849	12.1%
Diverse team	Treated group	1541	22%
Global North	Control group	40008	52.9%
Global South	Control group	18232	24.1%
Diverse team	Control group	17450	23.1%

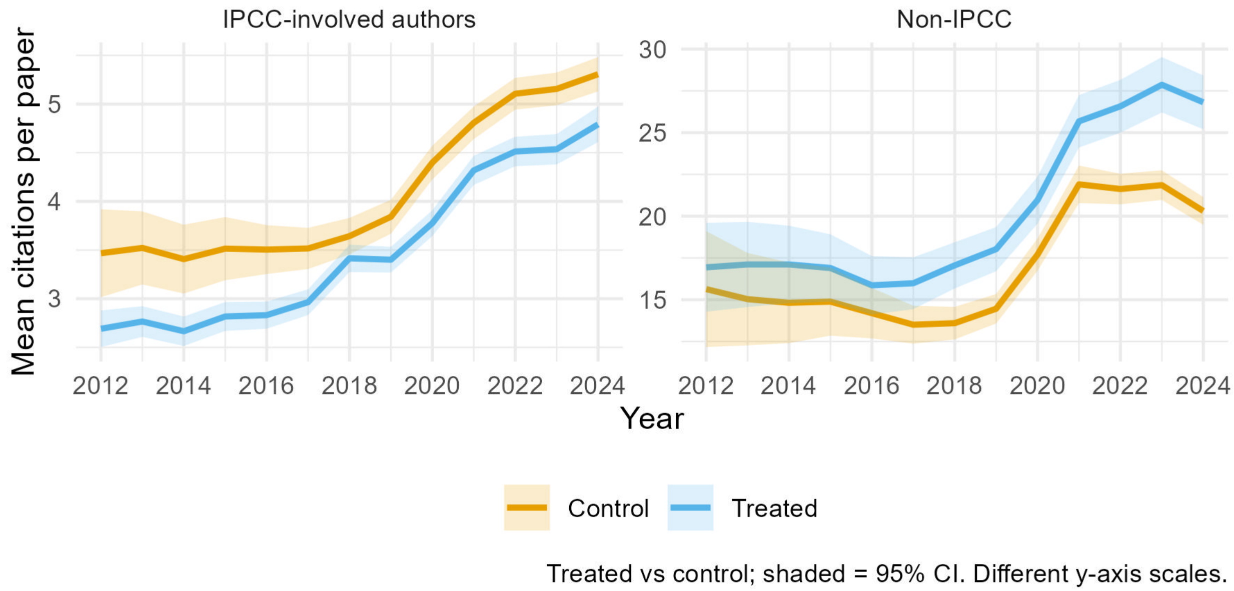
Figure 33: Dynamic impact of AR6 on citations on authors' region of origin



Note: The plot presents separate event-study estimates for disjoint samples of publications authored exclusively by Global North teams, exclusively by Global South teams, and by mixed teams including authors from both regions. 'All' refers to the full sample.

F.5 Citers

Figure 34: Average Citations per Paper Over Time, by IPCC Author Category (aggregated)



While the citer-level analysis is not conducted on the full panel of treated and control papers and count directly the individual citations, the resulting citation patterns shown in Figure 35, closely resemble those from the full-sample analysis which uses pre-aggregated citation counts by year. This similarity suggests that the analysis captures the majority of citations, that the panel is approximately balanced, and that the patterns by author category are likely representative of the full sample.

Figure 35: Average Citations per Paper Over Time for the restricted panel of citers analysis.

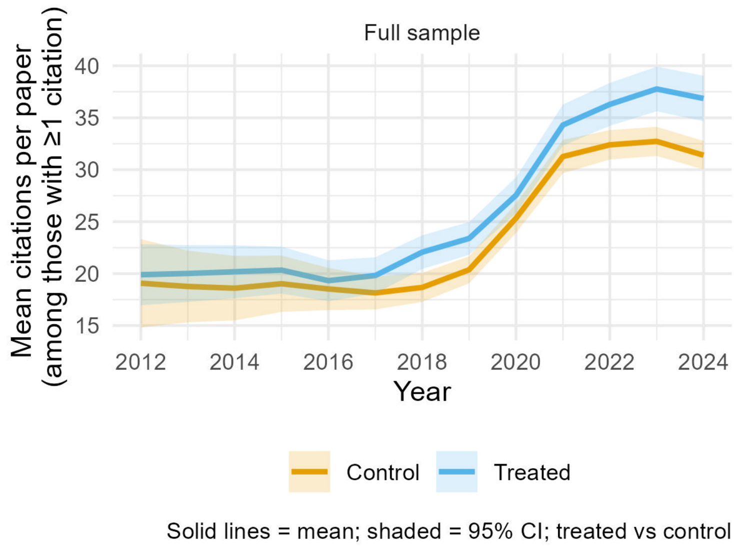
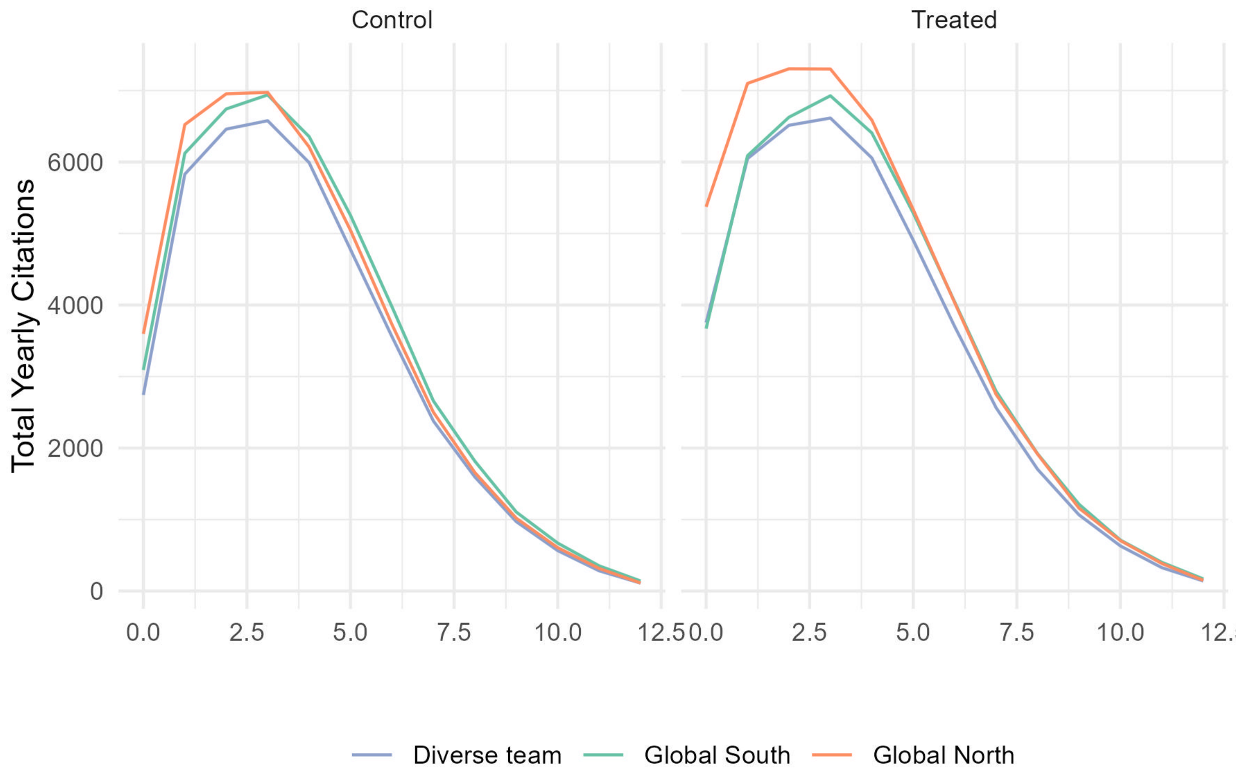


Figure 36 shows that the Global North accounts for most citations just after publications of the papers (the AR6 references), then reaches a plateau, while the Global South citations still increase, the two are at the same level 4 years after publications.

Figure 36: Total citations received by the control and treated group of AR6 references split by the institutions of the citing authors



G Topic analysis

G.1 Topics

For a subset of treated and control papers (same as for the authors info),: 7011 IPCC references papers and 75,693 control papers. From Open Alex, I get topic (linked to a larger subfield and field), one or two (rarely 3), with a score. I select the primary field (highest score).

The 7000 IPCC references paper cover 508 topics (as the primary, highest score topic), the control papers cover 2440 (some might be the same as the treated group). In both group, the most present topics are "Climate Change Policy and Economics", "Environmental Impact and Sustainability", and "Energy, Environment, and Transportation Policies".

G.2 Estimate of AR6 citation boost with topic restriction and topic FE

One question is I build the control group with only balance in journal x year. Is it biased with topics ? I would assume no, or not in the direction of a bigger effect, since social sciences and climate change papers on top of that, are among the least cited fields. But I perform three

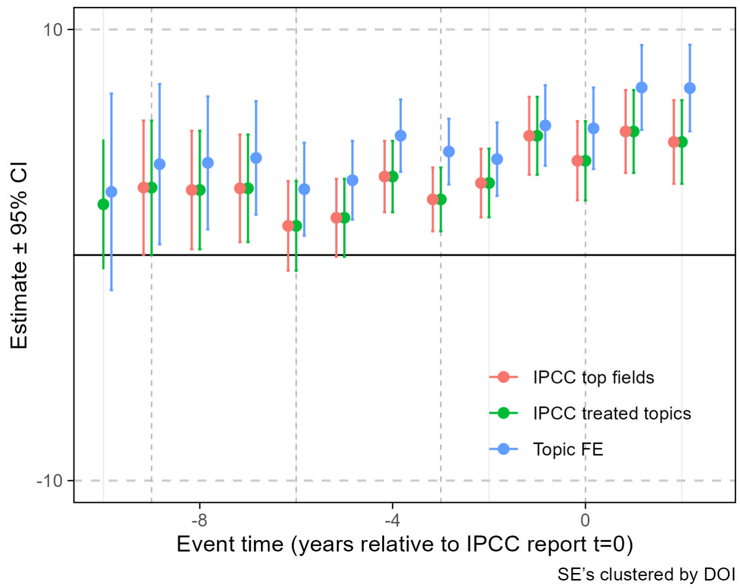


Figure 37: Including topic for AR6 WG3 citation boost estimate

robustness tests i) adding a topic fixed effect, ii) restricting to topics which are present in the IPCC references, iii) restricting to the 7 top fields of IPCC (thus excluding Medicine or Astronomy for instance).[16]

in Figure 37, I show that including or restricting based on topic does not change the result significantly.

G.3 Stylised fact

I am interested in whether the topics included in IPCC references have a different citation trajectory than the rest of the papers. The 7000 IPCC references paper cover 508 topics (as the primary, highest score topic), the control papers cover 2440

As I've shown that the effect of the IPCC publication starts in 2019-2020, I need to take care of exogenous elements in 2020 that might disrupt the trend: Covid and some new topics (e.g. AI), and more generally blatant outliers.

I excluded any topics related to COVID, as well as the fields Biochemistry, Genetics and Molecular Biology, Immunology and Microbiology, Medicine, and Computer Science. Additionally, I excluded the following specific topics: Computational Drug Discovery Methods, Algorithms and Data Compression, Lysosomal Storage Disorders Research, Advanced Chemical Physics Studies, and Topological Materials and Phenomena.

Figure 14 shows similar trends between the topics, whether they are included in IPCC or not. Levels are different though.

[16] In the order of importance: Environmental Science, Engineering, Economics, Econometrics and Finance, Energy, Social Sciences, Business, Management and Accounting, Agricultural and Biological Sciences.

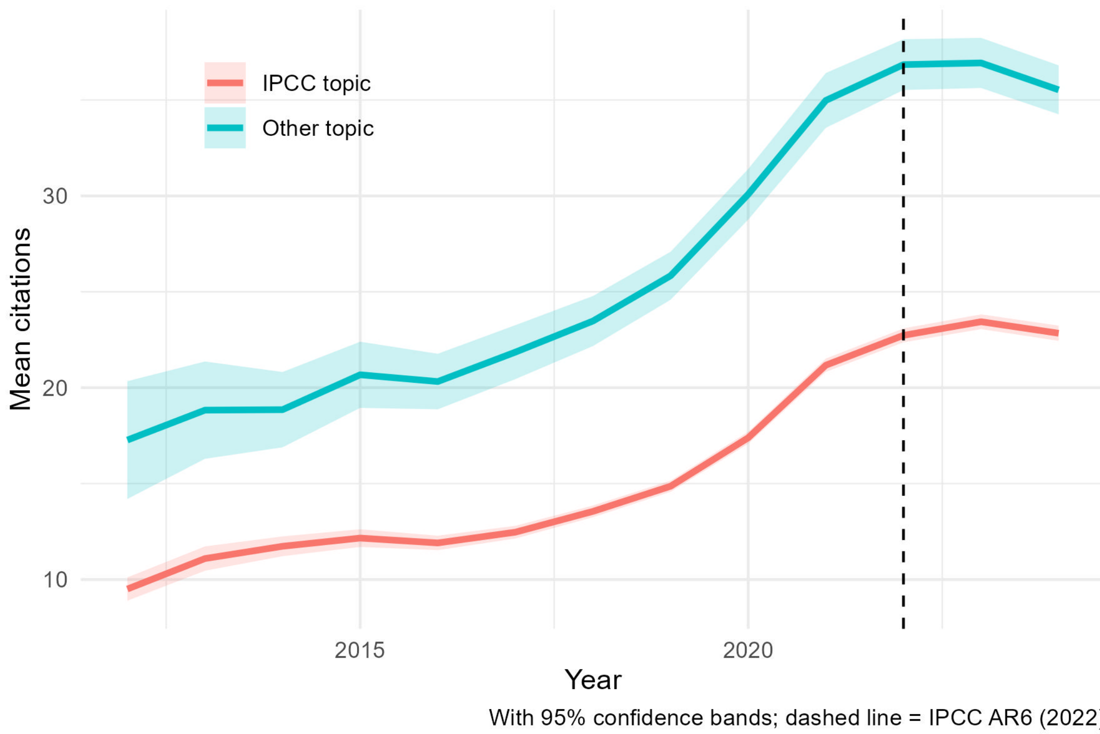


Figure 38: Yearly citations average and 1.96 × standard error for IPCC included topics and other topics

G.4 From event–study coefficients to the aggregate citation impact

The event–study estimates in Sections 3 and 7 yield two key coefficients for each event year k.

(i) $\hat{\beta}_k$ measures the *marginal change in citations to* non–IPCC *papers* when the fraction of papers in their topic that are IPCC-cited (*IPCC share*) rises by one unit.[17]

(ii) $\hat{\Delta}_k$ captures the *citation boost enjoyed by IPCC-cited papers themselves* at the same horizon.[18]

To assess whether the IPCC increases or merely redistributes scholarly attention, we aggregate these per–paper effects across topics. For non–cited papers the crowding-out term is $N_g^{\text{non}} s_g \hat{\beta}_k$, where N_g^{non} is the number of non-cited papers in topic g and $s_g \in [0,1]$ its IPCC share; the share enters because the effect is proportional to the intensity of treatment. For cited papers the gain is $N_g^{\text{cited}} \hat{\Delta}_k$, with no share adjustment ($s_g = 1$ by construction). Summing over topics and dividing by the total number of papers gives the normalised net impact

A first back-of-the-envelop approach to approximate the effect gives *crowding-out* and *boost* effects at $t = +1$ of

$$\hat{\beta}_{+1} = -20.0 \quad \text{and} \quad \hat{\Delta}_{+1} = +5.0,$$

[17] Formally, it is the coefficient on $\mathbf{1}\{t = k\} \times \text{IPCC-share}_{g(i)}$.

[18] The coefficient on $\mathbf{1}\{t = k\} \times \mathbf{1}\{\text{paper cited}\}$.

interpreted as follows: a one–unit increase in IPCC share ($s_g \to 1$) lowers a non-cited paper's 2023 citations by 20, whereas each IPCC–cited paper gains 5 citations.

Weighting these effects by the number of papers and the relevant shares,

$$\widehat{\mathrm{Net}}_{2023} = N_{2023}^{\mathrm{cited}}\,\hat{\Delta}_{+1} + \sum_g N_{g,2023}^{\mathrm{non}}\, s_g\, \hat{\beta}_{+1} = -65\,400 \text{ citations.}$$

Normalising by the 2023 paper count ($N_{2023} \simeq 125\,500$) gives an average loss of -0.52 citations *per paper*.

Repeating the calculation for each event year and stacking the two coefficient vectors produces the time-path plotted in Figure 39.

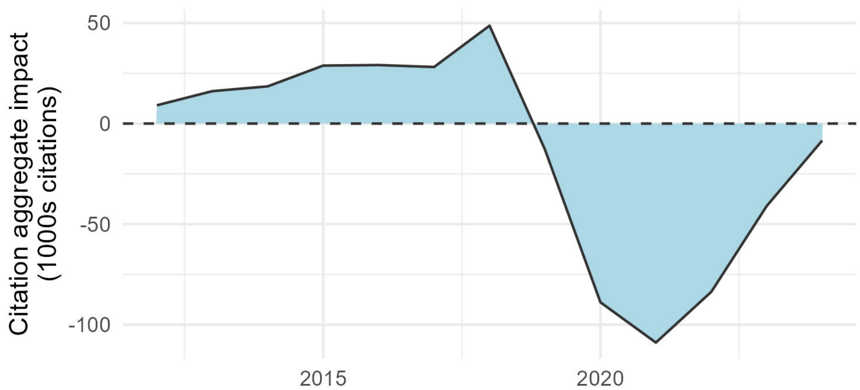


Figure 39: Yearly aggregate citation impact of IPCC across the topic it covers

To obtain confidence bands we draw $B = 10^6$ coefficient vectors from $N(\hat{\boldsymbol{b}}, \hat{\mathbf{V}})$, where $\hat{\mathbf{V}}$ is the block-diagonal variance–covariance matrix of the two regressions, and re-compute the net statistic for each draw Under the delta method (Wooldridge (2010), sec. 3.5.2, p44).

This yields a point estimate of -0.170 citations per paper and a 95% interval of approximately $[-0.582, 0241]$, confirming that the negative normalised net impact is not statistically distinct from zero.

Interpretation. Despite a modest gain of five citations for each IPCC-endorsed paper, the large pool of non-cited papers in partially treated topics suffers an average loss of roughly half a citation, yielding a negative net balance. The pattern is consistent with a reallocation of scholarly attention: IPCC endorsement concentrates citations on a handful of papers at the expense of their untreated neighbours.

H Focus on Economics journals and citations

Journal classification. To tag outlets as Economics or Non-economics, I combine threee lists. First, the CNRS Section 37 ranking (2020) places economics journals into categories 1–4; second, the 2022 LSE departmental lists rank journals used in tenure decisions across Economics, Geography and related fields; and, finally, the June 2025 RePEc roster provides the broadest catalogue of economics-relevant titles, extending to multidisciplinary venues such as Science, Nature, Nature Climate Change and PNAS. A journal is flagged "Economics" if it appears in either the CNRS list or RePEc.

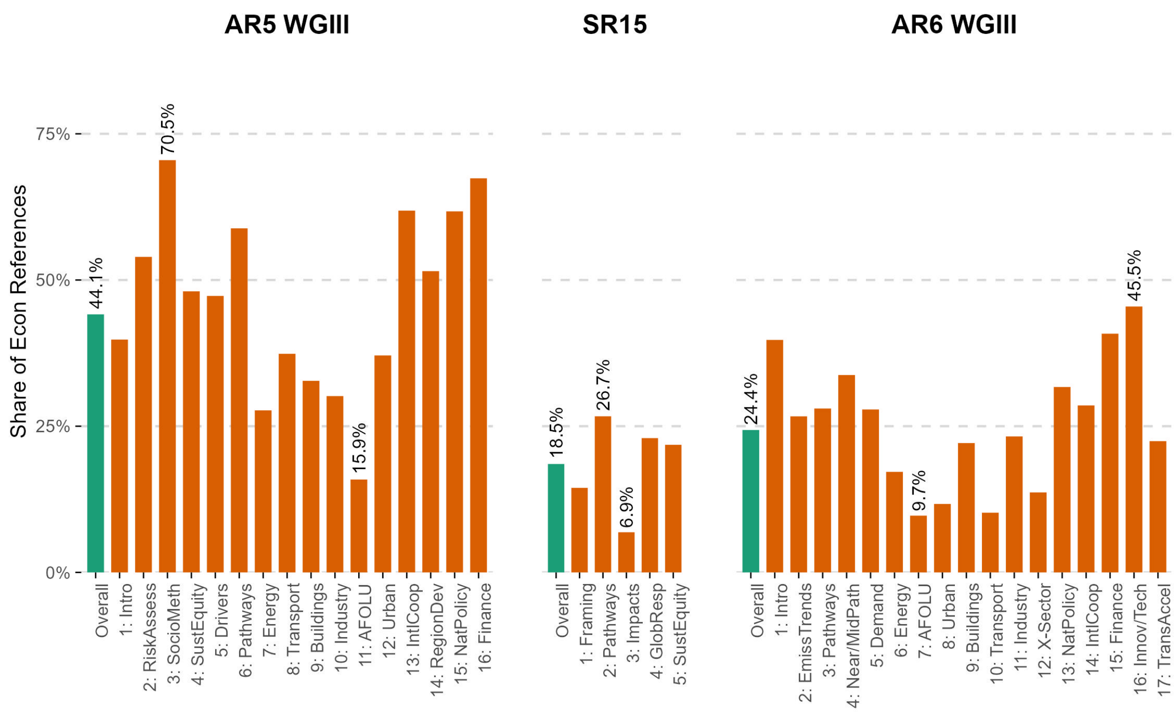


Figure 40: **Economic-Journal References in IPCC Reports (CNRS).** I use the CNRS Economics journal ranking to classify Economics references. It excludes the Nature family of journal, Science, PNAS. For a broader definition of economomics, as a journal where economic papers get published.

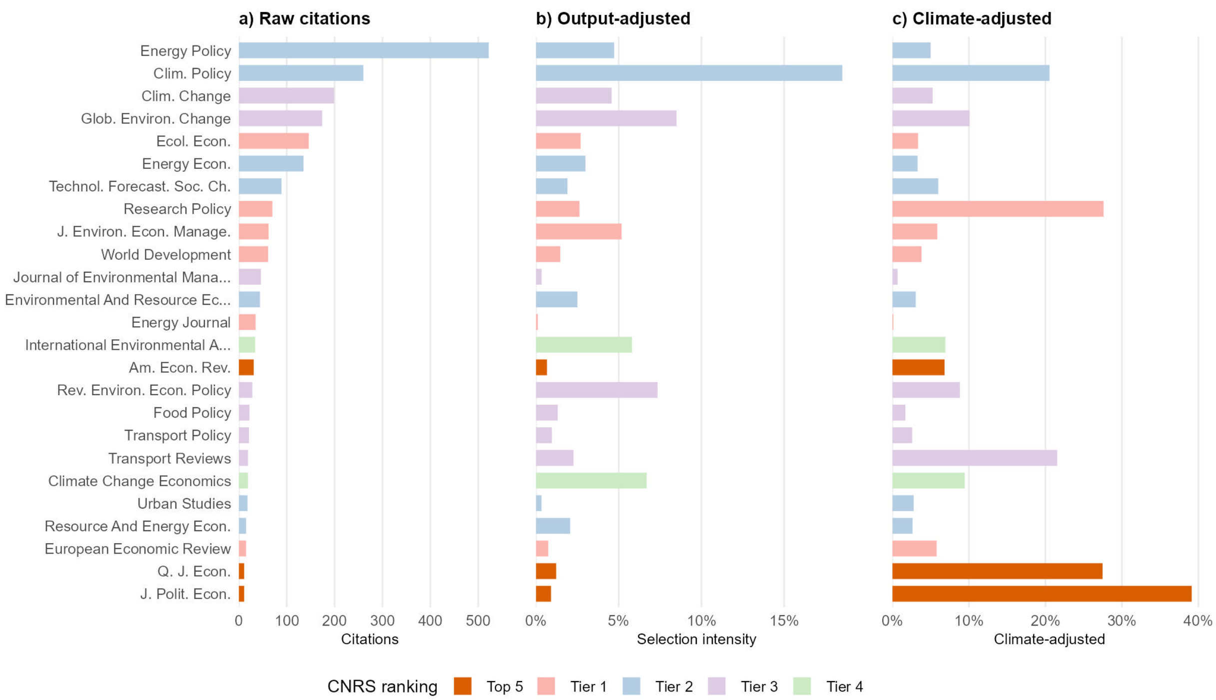


Figure 41: **Journal citation patterns in IPCC AR6 Working Group III for Economics journals.** Top 26 Economics journals and so-called Top 5 journals cited in AR6 WGIII, shown as absolute citation counts (**a**), normalised by average annual journal output (**b**), and normalised by climate-relevant output (**c**). Colour indicates journal quality tier the CNRS 2020 journal ranking in 4 tiers.