Which science reaches the IPCC?
Expert recruitment and evidence selection

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Abstract

Expert assessments shape the evidence presented to policymakers, and their citations increasingly inform evaluations of research impact, but the scientists who assemble this evidence also contribute to the literature they assess. I examine how journal standing, scholarly visibility and expert recruitment relate to evidence selection, using more than 27,000 references from the 2014 and 2022 climate-mitigation assessments of the Intergovernmental Panel on Climate Change (IPCC). Specialist journals, rather than the most prestigious ones, supply much of the evidence, largely from venues in which assessment authors publish. Within the same journal, year and topic, prior scholarly attention predicts inclusion, while papers coauthored by appointed lead authors have more than three times the odds of inclusion after accounting for prior citations and author geography. In all 14 chapters matched across the two assessments, bibliographies shift towards research by experts joining the writing team and away from research by those leaving it. Experts appointed for a chapter's subject are cited more in it than elsewhere in the report, but those who write the chapter are cited there more than twice as intensively. The selection of experts is therefore part of the selection of evidence, and assessment citations reflect institutional choices as well as research uptake.

Keywords: Expert assessment; IPCC; Evidence selection; Research evaluation; Science–policy interface; Policy citations; Bibliometrics

1 Introduction

Expert assessments transform extensive scientific literatures into bodies of evidence that inform policy. In doing so, they necessarily select which research is assembled, compared and presented to decision-makers (Jasanoff, 1990). The Intergovernmental Panel on Climate Change (IPCC) is the most well-known and provides assessments every six to eight years, and governments, negotiators and researchers rely on them. In 2025, the International Court of Justice identified IPCC reports as the best available science on climate change (ICJ, 2025), so research cited in these reports now also carries legal weight. Selecting evidence is especially tricky for the IPCC's Working

Group III (WGIII) which assesses politically sensitive subjects, such as climate-change mitigation performances across technologies, economic sectors, policy instruments and institutions. Its authors must synthesise a large and fast-growing literature in engineering, economics, innovation studies and other social sciences (Callaghan et al., 2020; Minx et al., 2017). What enters an assessment, and what does not, therefore matters both for policy and for the field being assessed, because it helps determine which studies are treated as central and which research communities gain visibility and influence (Vasileiadou et al., 2011; Doran et al., 2023; Amarante et al., 2022; Baninla et al., 2022; Aigner et al., 2025).

This paper examines which scientific research enters the IPCC's climate-mitigation assessments, how it is distributed across journals and papers, and how it relates to the experts who write the reports. I reconstruct more than 27,000 references cited in the Working Group III contributions to the Fifth and Sixth Assessment Reports, hereafter noted as AR5 (IPCC, 2014) and AR6 (IPCC, 2022). I compare the journals cited by the IPCC with those in which its authors publish, and cited papers with uncited papers from the same journal, publication year, and topic. Finally, I follow 14 matched chapters across the two assessments to examine whether changes in writing teams are accompanied by changes in the representation of incoming and outgoing authors' research, including work published before the new teams were appointed.

Since 1988, the IPCC's expert-panel model has been adopted for biodiversity (IPBES, 2019; Hughes and Vadrot, 2019), for chemicals, waste and pollution (ISP-CWP, 2025), and for artificial intelligence (IISPAI, 2025; Government of Canada, 2018; Bengio et al., 2025). Artificial intelligence is expected to participate more and more in synthesising evidence, including for the forthcoming IPCC Seventh Assessment Report (AR7) (Buck et al., 2026; Callaghan et al., 2025; Lück et al., 2025). The question of literature selection therefore extends to science–policy interfaces in general and to their credibility (Cash et al., 2003).

The relationship between experts and the research they evaluate is a longstanding concern in the economics of scientific evaluation. Expertise provides information about research quality, but it can also influence which work receives attention and how it is judged. Grant reviewers are better informed about, but also more favourable towards, research in their own fields (Li, 2017). Journal editors publish more papers by professionally connected researchers, although those papers subsequently attract more citations (Laband and Piette, 1994; Brogaard et al., 2014), while peer reviewers favour researchers within their professional networks (Teplitskiy et al., 2018). Proximity does not invariably produce favourable assessments: experimentally assigned evaluators have also been found to score proposals closer to their own expertise more harshly (Boudreau et al., 2016). The extreme case of proximity is authors citing their own work. Such self-citation is common and generally legitimate (Glänzel et al., 2006), it works and increases visibility. Authors who cite themselves more are also cited more by others (Fowler and Aksnes, 2007), and self-citation increases when citations count for careers (Seeber et al., 2019). In expert assessments, the experts also choose which research enters the evidence base in the first place.

Prior research on the IPCC has documented the rapid topical expansion of climate research (Callaghan et al., 2020; Grieneisen and Zhang, 2011; Minx et al., 2017), examined early IPCC citation patterns (Bjurström and Polk, 2011), and critiqued persistent disciplinary, regional and gender imbalances among IPCC authors (Hughes and Paterson, 2017; Hughes and Vadrot, 2019; Corbera et al., 2016; Pollitt et al., 2024; Gay-Antaki and Liverman, 2018; Tandon, 2023).

Bibliometric studies have also found substantial overlap between assessment authors and frequently cited researchers (Jankó et al., 2017; Asatani et al., 2026). These studies show who takes part in assessments and whose research is cited. They say little about which literatures gain visibility through IPCC citation, or how this changes from one report to the next.

Because the IPCC repeats its assessments, I can follow this relationship over time. Although successive reports cover broadly comparable subjects, their writing teams change substantially: in the 14 matched chapters, 83% of AR6's appointed lead authors had not served on the corresponding AR5 chapter. Chapter outlines are agreed before authors are appointed, and experts are then recruited to cover the agreed scope while balancing expertise, geographical representation and perspectives (IPCC, 2012; IPCC Working Group III, 2018). Comparing successive bibliographies therefore reveals whether the prominence of researchers' publications remains stable across writing teams or shifts towards those appointed to the new assessment. Unlike the editor rotations studied by Brogaard et al. (2014), changes in writing teams do not by themselves isolate the effect of participation, since incoming authors may be cited more because their research is particularly relevant to the assessment or because their involvement in drafting brings greater attention to their work. To separate the two, I compare the writers with experts appointed for the same subjects who did not write the chapter.

The results reveal three patterns. First, the assessment draws heavily on specialist journals, many of which are also prominent in its authors' publication records. Journal prestige does not consistently predict assessment uptake, while prestigious generalist journals are more prominent in the references of IPCC-cited papers than in the assessment's own bibliography. Second, within journals, papers linked to appointed IPCC authors are disproportionately represented. Publications coauthored by an AR6 lead author have between three and six times the odds of inclusion of comparable papers from the same journal and year, including within the same topic and after accounting for prior citations and author geography. Papers with greater prior scholarly visibility are also more likely to be included, while Global South-only research teams are less represented than Global North-only teams in comparable journal-year samples.

The main finding comes from the comparison of successive writing teams. In all 14 matched chapter pairs, the share of references linked to incoming authors rises between AR5 and AR6, while that linked to outgoing authors falls. Pooled across chapters, incoming authors' shares increase from 3.8% to 11.5%, while outgoing authors' shares decline from 12.3% to 4.0%. This reversal is not explained by differences in group size, holds for lead authors appointed before drafting, and is limited to the chapters authors write. It is strongest for recent publications but remains detectable in older literature. The lead authors' citations are also more than twice as concentrated in the chapter they write as those of the AR5 and AR7 lead authors of the same chapters, and almost three times as concentrated as those of its Review Editors.

This paper contributes to three strands of research. First, it contributes to the literature on the organisation and biases of expert assessment. The closest studies document concentration at several levels: most of the researchers cited most frequently in the AR5 physical-science report participated in writing it (Jankó et al., 2017), a small group of scientists, many serving on advisory bodies such as the IPCC, supplies a large share of the research cited by intergovernmental organisations (Asatani et al., 2026), and within Working Group III economics and integrated assessment modelling are prominent in both authorship and the evidence assessed (Hughes

and Paterson, 2017; Gusheva et al., 2024). I follow successive writing teams and show that bibliographic recognition moves with the experts responsible for each report. The selection of authors is therefore part of the selection of evidence, alongside the judgements made during drafting. Second, it extends research on expert evaluation (Li, 2017; Brogaard et al., 2014; Teplitskiy et al., 2018) from how experts judge research to which research receives consideration in the first place. The IPCC's successive assessments show that changes in expert teams are accompanied by changes in whose research enters the evidence base. Third, the paper contributes to debates on research evaluation. Academic rewards place considerable weight on publication in prestigious journals (Heckman and Moktan, 2020; Trueblood et al., 2025), yet journal standing does not map consistently onto the research used in assessments. Recognising contributions to expert assessments could complement journal-based evaluation and give greater credit to research that contributes to usable scientific knowledge (Clark et al., 2016), using policy-document citations as indicators of such broader impact (Bornmann et al., 2016; Szomszor and Adie, 2022).

The rest of the paper is organised as follows. Section 2 describes the setting and data, Section 3 the empirical strategy, Section 4 the results, and Section 5 their implications for research evaluation and assessment practice.

2 Institutional setting and data

2.1 Selecting, writing and reviewing the IPCC's mitigation assessments

Working Group III (WGIII) assesses the scientific literature on climate-change mitigation (IPCC, 2014, 2022). Its chapters are prepared by Coordinating Lead Authors (CLAs) and Lead Authors (LAs), who share responsibility for their content. Coordinating Lead Authors coordinate the preparation of chapters, while Lead Authors synthesise the literature and produce designated sections. They recruit Contributing Authors (CAs), who provide specialised expertise, text, figures and data. Review Editors (REs) oversee the treatment of comments received during the review process (IPCC, 2012). For AR6, each chapter has between 2 and 3 Coordinating Lead Authors, 7 to 15 Lead Authors, and between 3 and 60 Contributing Authors (25 on average).[1]

The composition of these teams follows a sequential selection process. First, the IPCC Panel approves the report outline (in September 2017 for AR6). Second, national focal points, the IPCC Bureau, and observer organisations nominate experts (IPCC, 2017). The WGIII Bureau then selects CLAs, LAs and REs, matching candidates' expertise to the report's sections (January 2018), while ensuring representation of different scientific perspectives, geographical and gender balance, and a mixture of new and experienced IPCC participants (IPCC, 2011, 2012). Third, once appointed, CLAs and LAs recruit CAs to complement their expertise, also considering geographical and gender diversity (IPCC, 2012). Author renewal therefore depends on more than individual records or willingness to serve. Authors must fit the report's outline, and the Bureau balances gender, country and the share of new participants. The AR6 selection report records

[1]The published report credits 36 CLAs, 163 LAs and 38 REs, plus 354 CAs (IPCC, 2022). These are counts of people per role. No one is a CLA or LA in more than one chapter but a CLA or LA can also be a Contributing Author elsewhere, and Contributing Authors can serve in several chapters. Table 1 counts each person once, under their highest role. In the published report, some experts appear in up to six chapters, or eight sections when the Summary for Policymakers, Technical Summary and annexes are included.

that 45% of the 226 experts selected were new to the IPCC, against 72% of those selected for AR5 (IPCC Working Group III, 2018).

The assessment process compounds two selection processes: the composition of the expert teams and the selection of scientific evidence by those teams.

2.2 IPCC references

I have recovered every reference cited in two recent IPCC volumes (AR6 WG III 2022 and AR5 WG III 2014) and match those references to external bibliometric databases. Full replication code and raw outputs are archived online. Supplementary Section S1 describes reference extraction, journal matching, author disambiguation and the construction of each sample.

The IPCC does not provide a machine-readable format of the references it cites. Each chapter ends with a two-column bibliography. I extract individual references from chapter bibliographies using an automated PDF-parsing procedure, detailed in Supplementary Section S1. The same routine (with minor tweaks for punctuation quirks in AR5) yields 18,047 reference instances in AR6 and 9,391 in AR5, covering 15,643 and 8,806 distinct works (Table 1). References are deduplicated within each report; repeated appearances across chapters are retained when the analysis concerns chapter bibliographies.

I matched references to OpenAlex (Priem et al., 2022), a fully-open index of scholarly works, by DOI or, failing that, by title, journal, yearly citation count, and year, with manual review of ambiguous cases. This identified 10,905 AR6 and 5,107 AR5 works with their publication year, topics, authors, and affiliations. I was able to retrieve the full reference lists of 9,800 AR6-cited papers from OpenAlex: 476,783 entries pointing to 235,739 distinct works. Papers with and without a retrieved list have similar publication years and similar shares in the most-cited journals, so the missing lists are unlikely to bias the comparison.

I harmonise journal names across reports, resolving inconsistencies in abbreviations, spelling and formatting before matching them to OpenAlex (Supplementary Section S1). Using OpenAlex, I retrieve the annual output of each identified journal and their share of climate-related papers using OpenAlex topic classifications. I measure journal prestige using the 2021 SCImago Journal Rank (SJR), a citation-weighted indicator of journal standing, applying the same measure to both assessments. Journals were also grouped by disciplinary and topical focus (Supplementary Section S1.5).

2.3 IPCC Authors

In the published AR6 and AR5 reports, I recover the full author list from the first page of each chapter, manually checking the accuracy of the information. For AR7, the Coordinating Lead Authors and Lead Authors are taken from the IPCC author database.

The chapter credits also list the countries of each author's affiliations, which I classify with the same country list used for the cited papers. Of the 227 people credited as AR6 WGIII Coordinating Lead Authors or Lead Authors anywhere in the report, 37.0% list affiliations only in the Global South, 52.4% only in the Global North and 10.6% in both. Including Contributing Authors lowers the Global South-only share to 26.3%, because those recruited during drafting are more often based in the Global North. These shares describe affiliations at the time of the

Table 1: Reference and author coverage.

	AR5	AR6	Total
References			
Reference instances across chapters	9,391	18,047	27,438
Distinct works within report	8,806	15,643	24,449
Distinct works with a normalised DOI	4,594	11,199	15,793
Distinct works with a recognised journal	5,107	10,905	16,012
Journals represented	799	1,334	2,133
Credited people			
Coordinating Lead Authors	34	36	63
Lead Authors	200	163	305
Contributing Authors	172	268	411
Author credit only outside chapters[a]	18	15	26
Review Editors without an author credit	37	31	50
All credited people	461	513	855
of which author sample[b]	424	482	805

[a] Author credits only in the Summary for Policymakers, Technical Summary or annexes, or a chapter Review Editor who holds an author credit there. [b] Coordinating Lead, Lead and Contributing Authors and the authors in note *a*; Review Editors without an author credit are excluded.
Note: Distinct works are deduplicated within, not across, reports. Reference instances retain repeated appearances across chapters. DOI and journal coverage is incomplete for books, reports, other grey literature and unmatched records. For references, the last column adds the two reports, so items appearing in both are counted twice: 402 works with the same DOI and 478 journals. For people, it counts each person once: 119 people are credited in both reports (101 of them in both author samples). People are identified by surname and first initial. Within a report, each person is counted once under their highest role in chapters 1–16 (AR5) or 1–17 (AR6); in the last column, under their highest role in either report.

report, not nationality.

For each AR6 author, I retrieve from OpenAlex their full bibliography published between 2000 and 2020, combining name-based queries with manual validation.[2] For each of the 444 validated authors, I retrieved all associated works published within the study window, yielding 44,809 total publication records.

3 Empirical strategy

I examine which research IPCC Working Group III cites at three levels: the journals it draws on, the papers it selects within a journal, and the author teams whose own work it cites, across 14 chapters matched between AR5 and AR6 (Supplementary Table S2).

3.1 Journals, publication output and secondary references

The broadest view of where the IPCC's evidence comes from is the journals in which it is published. Each journal represents a research community with its own topics, methods, and networks. If authors screening the literature use journal reputation as a quality signal, or if prestigious journals publish more rigorous or relevant work, they should be over-represented relative to their size. I divide each journal's AR6 references by its 2005–2021 output as some journals publish very few papers (about 50 papers a year for the *Quarterly Journal of Economics*,

[2] Automated author search frequently returned homonymous or highly cited authors with identical names; all author profiles were therefore automatically disambiguated using IPCC-related published works to select the most likely candidate.

against about 1,700 for the *Journal of Cleaner Production*). To compare specialist outlets such as *Climate Policy* with generalist ones such as *Science*, I further divide by each journal's estimated climate-related output (robustness checks with data from Henry (2025): Supplementary Section S1.6).

Generalist journals may also reach the assessment indirectly, through the papers that cite them. I compare each journal's ratio of entries in the reference lists of the 9,800 AR6-cited papers to its direct AR6 citations with the pooled ratio.

Authors may also draw on the journals they know best and in which they publish. I compare each journal's AR6 reference–chapter count with the 2000–2020 publications of the 444 matched AR6 authors against the pooled ratio.

3.2 Selection among papers in the same journal

I compare cited and uncited papers within the same journal, this removes the journal fixed effect. I test whether a paper is more likely to be included in the assessment if it was more visible before the assessment started (pre-2018). This is a version of the Matthew effect, whereby citations accumulate on work that is already visible (Merton, 1968; Azoulay et al., 2014). The IPCC also seeks geographical balance among its authors (Section 2). I test whether that balance extends to the literature it cites, and whether papers by Global South authors are favoured to achieve it. I classify author teams with the NORRAG country list (NORRAG, 2023) and add international coauthorship and team size. Finally, I test whether papers coauthored by the assessment's authors (either in the full report or in the chapter citing them) are more likely to be cited than comparable papers from the same journal.

I compare AR6-cited papers published in 2012–2017 with randomly sampled uncited papers from the same journal and year and, in stricter specifications, the same primary subfield or topic, keeping at least three controls per cited paper. For paper i in comparison set s, I estimate a conditional logit model

$$\operatorname{logit} \Pr(Y_{is} = 1) = \alpha_s + \beta_c \log_2(1 + c_i) + \boldsymbol{z}_i'\boldsymbol{\gamma}, \tag{1}$$

where $Y_{is} = 1$ when AR6 cites the paper, c_i counts its citations through 2017, so that β_c is the change in log odds per doubling of $1 + c_i$, and $\boldsymbol{z}_i$ holds the other covariates; standard errors are clustered by journal. The estimates are relative odds among sampled papers, not inclusion probabilities.

3.3 Author turnover and bibliographic alignment

A preference for the experts' own papers may reflect prominent researchers whom any team would cite, or the team writing each chapter. Author turnover between AR5 and AR6 separates the two. A matched chapter covers the same subject in both reports, so if citations followed subject expertise alone, the reference shares of outgoing authors, who served only on the AR5 chapter, and incoming authors, who joined its AR6 successor, should not change. If the incoming share rises and the outgoing share falls, alignment moves with the writing team.

I match 14 AR6 chapters to their closest AR5 counterparts (Supplementary Table S2) and exclude continuing authors. The main specification uses the full credited team (Coordinating Lead,

Lead and Contributing Authors), all of whom supply text and references. Because Contributing Authors are recruited during drafting, sometimes for material already being assessed, I also report every estimate for Coordinating Lead and Lead Authors only.

For chapter pair c, let E_c and X_c denote the incoming and outgoing groups, and $s_c^k(A)$ the share of references in report k naming at least one member of group A; a paper coauthored by both groups enters both shares. The two-cycle contrast

$$T_c = \underbrace{\left[s_c^{AR6}(E_c) - s_c^{AR5}(E_c)\right]}_{\text{Change for incoming authors}} - \underbrace{\left[s_c^{AR6}(X_c) - s_c^{AR5}(X_c)\right]}_{\text{Change for outgoing authors}}$$

is positive when each chapter's own authors appear on more of its references than the other group; I report it with each group's raw change. Because larger groups are more likely to appear, I reallocate each pair's pooled incoming and outgoing authors 9,999 times to groups of the observed sizes, using the same draw for both bibliographies, and subtract the mean reallocated gap.

The main estimate is the equally weighted mean contrast $\bar{T} = \frac{1}{14}\sum_c T_c$ (reference-weighted estimates: Supplementary Section S3). Inference treats the chapter pair as the unit of observation: I resample the 14 pairs with replacement (49,999 draws), keeping each pair's two bibliographies and two author groups together and holding its size benchmark fixed, and report the 2.5th and 97.5th percentiles of the resampled $\bar{T}$. Intervals for individual pairs instead resample references within each bibliography (9,999 draws), holding rosters fixed (Supplementary Section S1.10).

The shift could still reflect the relevance of the writers' work. I therefore compute how concentrated each group's citations are in its matched chapter relative to the rest of the report (the share of the chapter's AR6 references naming a member, divided by the same share in the other matched chapters). I compare AR6 writers to experts who did not write the chapter: the chapter Review Editors, appointed at the same time through the same process, and the Coordinating Lead Authors and Lead Authors of the corresponding AR5 and AR7 chapters. Relevance raises every group's concentration; assuming the comparison groups' work is as relevant to the chapter as the writers', the writers' excess concentration measures the effect of writing it. Supplementary Section S3.9 compares the output and research profiles of incoming and outgoing authors.

4 Results

Section 4.1 reports the journal-level results, Section 4.2 the paper-level results and Section 4.3 the writing-team results.

4.1 Journal reputation and citations

4.1.1 Prestige and citation intensity

AR6 contains 10,905 journal-identified papers across 1,334 journals. In absolute terms, *Energy Policy* leads with 522 references, followed by *Environmental Research Letters* (349) and the *Journal of Cleaner Production* (325). The prestigious multidisciplinary journals appear further

down the list: *PNAS* contributes 142 references, *Science* 116, and *Nature* 110, each about 1% of the journal-identified total (Figure 1A).

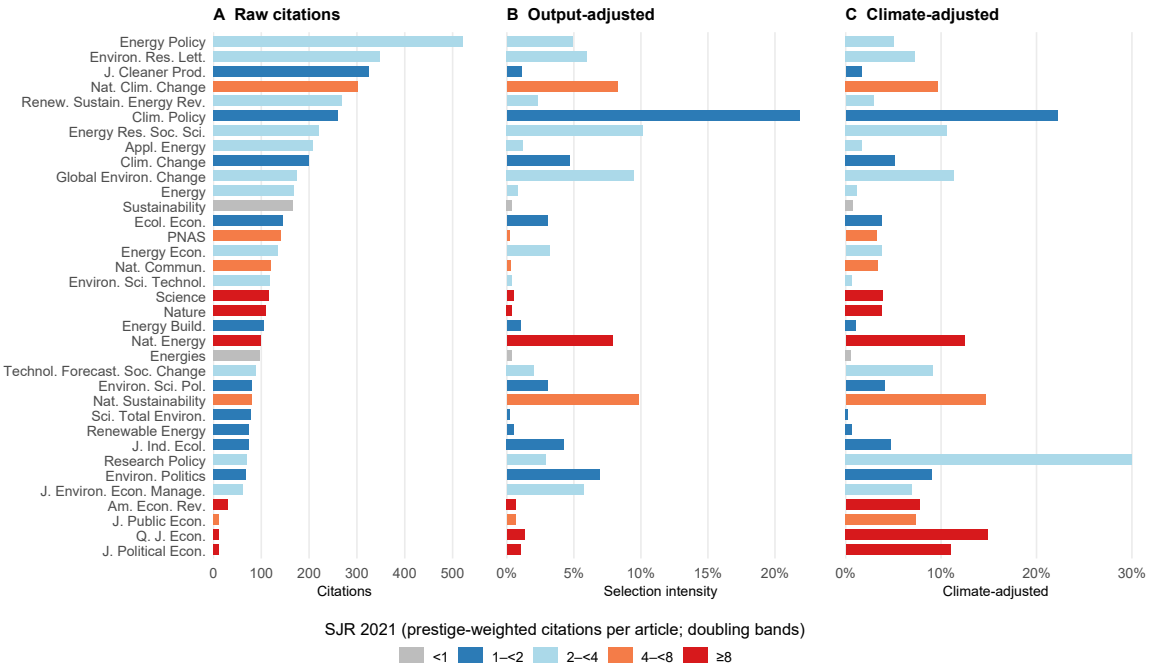


Figure 1: **Journal prestige and AR6 citation intensity.** The display includes 35 frequently cited journals, with selected economics journals included by design, ordered by the number of distinct references in AR6 WGIII (A). Panel B divides these references by the journal's publication output during 2005–2021, excluding errata, book reviews and other non-research items; panel C divides them by estimated climate-relevant output during the same period. Colour shows the journal's 2021 SJR score in fixed doubling bands. SJR is a citation-based prestige measure rather than an assessment of mitigation relevance. Climate-adjusted ratios for generalist journals can rest on small estimated denominators.

Adjusting for publication volume changes the ranking (Figure 1B). AR6 cites the equivalent of 22% of the papers *Climate Policy* published during 2005–2021. *Nature Climate Change* overtakes *Energy Policy*. High-volume journals fall sharply: the *Journal of Cleaner Production*, third in raw references, has an output-adjusted intensity of 1.1%, and *Sustainability* 0.4%. Journal prestige does not predict these intensities. *Nature Energy* and *Nature Sustainability* combine high citation intensities with high SJR scores, while *Climate Policy*, *Energy Research & Social Science* and *Environmental Politics* are cited heavily despite lower scores. *Nature* and *Science*, with some of the highest SJR scores in the sample, are cited at about 0.4 and 0.5 references per 100 published papers.

The same comparison extends to a larger subset: 146 journals with at least ten cited works across the two reports, for which publication output was retrieved, and a 2021 SJR score (Supplementary Table S4). They are a small fraction of the 1,334 cited journals but supply 7,657 of the 10,905 journal-identified AR6 references (70.2%); the comparison therefore describes the journals that carry most of the bibliography. Over these 146 journals, SJR is not associated with citations relative to publication volume: the Spearman correlation is 0.08 ($P = 0.35$) using publication output and 0.08 ($P = 0.31$) using research articles and reviews only, and log–log elasticities are close to zero with and without subject-area fixed effects. Restricting the sample to journals registered as peer-reviewed channels leaves the estimates essentially unchanged.

Normalising by estimated climate-related output produces a positive association with SJR among the 50 journals for which a climate share is available (Spearman $\rho = 0.44$; Figure 1C), but the association is largely induced by the denominator. In the same journals, output-adjusted intensity is unrelated to SJR ($\rho = -0.03$), while the estimated climate share declines with it ($\rho = -0.49$): the high-SJR journals in this sample are generalist outlets that publish relatively little on climate. Several of the highest ratios rest on such small shares, estimated from topic keywords: *Research Policy* (70 AR6 references against an estimated 233 climate-related papers), the *Journal of Economic Perspectives* (13 against 65) and the *Quarterly Journal of Economics* (11 against 74). The association is robust to removing the general-interest economics journals or the journals with the fewest climate-related papers (Supplementary Section S2.1).

4.1.2 Secondary references

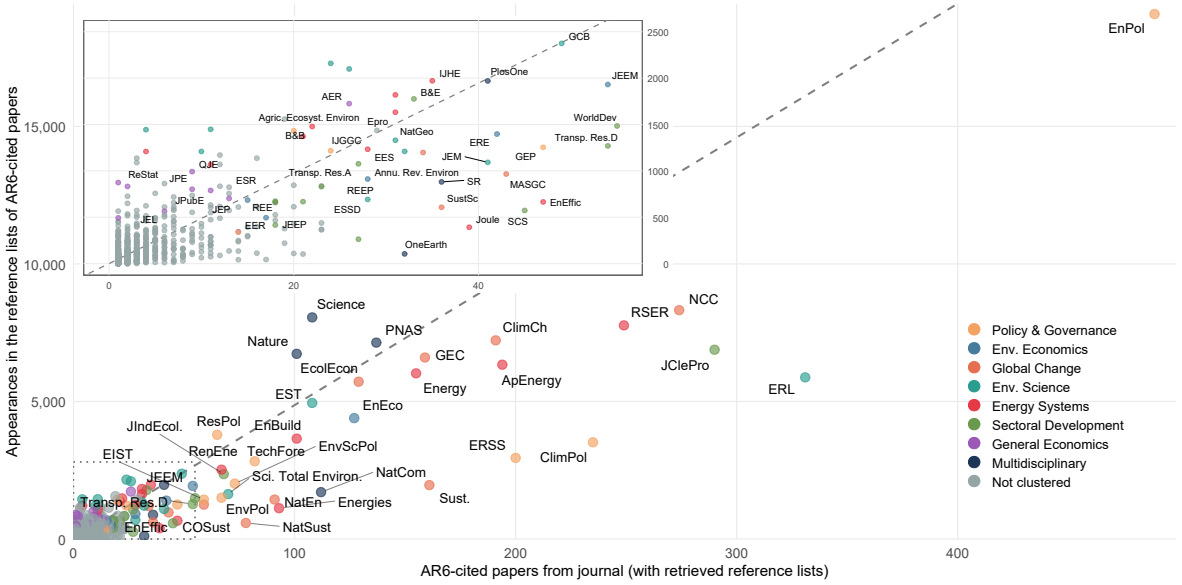
For each paper cited by the IPCC, I analyse its list of references. Specialist journals are prominent in both the direct and secondary layers, but some generalist journals, including *Nature* and *Science*, appear more prominently in the secondary distribution (Figure 2). Among sources with recovered reference lists, *Nature* supplies 101 directly cited papers and 6,732 entries in the bibliographies of the cited papers. Relative to the pooled ratio of about 49 secondary entries per direct source, its secondary presence is larger. The *Journal of Environmental Economics and Management* and *World Development* show the reverse pattern: their direct presence is larger relative to their secondary presence.

Articles can contribute to the assessment through two channels. Secondary references may identify research that informs the methods or concepts of directly cited papers, but the citation counts do not establish what was transmitted to the IPCC text. They do show that a journal's place in the direct bibliography can differ from its place in the literature cited by those sources.

4.1.3 Authors' publication venues

Of 13,131 journal-identified reference–chapter instances, 12,088 (92.1%) concern journals in which at least one matched AR6 author published during 2000–2020. This is a broad overlap measure across a large author pool and a long publication window. The remaining instances come from 505 journals. They include outlets beyond the authors' usual venues, in bioenergy, building research, technology management and climate law, and several general-interest economics journals, among them the *Journal of Political Economy*, the *Quarterly Journal of Economics* and the *Review of Economics and Statistics*, in which no matched author published during the window. A few residual journal-name variants also fall in this group, so the 92.1% is a lower bound.

The distribution nevertheless differs from the authors' publication record (Figure 3). Relative to the pooled reference-to-publication ratio, *Nature Energy* is cited at about six times the proportional benchmark, and *Nature Sustainability* and *Nature Climate Change* at about four times. *Energy Policy*, where IPCC authors publish most, is cited at more than twice that benchmark. *Research Policy* and *Joule* also contribute more references than their shares of author publications would imply. The assessment bibliography draws heavily from journals represented in its authors' research, while assigning those journals different weights from their publication records. The weights also differ across chapters: framing, sectoral and cross-cutting



EnPol: Energy Policy; ERL: Environmental Research Letters; RSER: Renewable and Sustainable Energy Reviews; NCC: Nature Climate Change; JClePro: Journal of Cleaner Production; ApEnergy: Applied Energy; ClimCh: Climatic Change; ClimPol: Climate Policy; GEC: Global Environmental Change; GEP: Global Environmental Politics; ERE: Environmental and Resource Economics; GCB: Global Change Biology.

Figure 2: **Direct and secondary citations by journal.** Distinct AR6-cited papers from each journal among the 9,800 with retrieved reference lists, against that journal's appearances in those reference lists. The dashed line marks about 49 secondary entries per primary paper; the inset enlarges low-volume journals. Colours denote journal clusters (Supplementary Table S1); the most frequent abbreviations are spelled out under the figure, and the others are listed in Supplementary Section S5.

chapters draw on different journal communities, with *Energy Policy* one of the few outlets prominent throughout (Supplementary Figure S3). Because chapters on different topics draw on different journals, I compare writing teams across chapters on the same subject in Section 4.3.

Topic fit alone would produce this overlap between the literature that the assessment cites and the literature that its authors publish: experts on mitigation publish where mitigation research appears, and an assessment of that research cites those journals. Journal-level counts cannot show whether the experts' own papers are favoured over comparable work in the same venues, which is addressed by the paper-level comparisons in the next section.

4.2 Selection within journals

Holding the journal fixed, Table 2 compares AR6-cited papers published in 2012–2017 with uncited papers from the same journal and year and, in stricter specifications, from the same primary subfield or topic, accounting for prior citations, author geography and team characteristics (Section 3.2).

4.2.1 Author links

Across the journal–year, subfield and topic specifications, papers linked to an appointed AR6 lead author have 3.26–6.18 times the odds of inclusion, while papers linked only to other credited participants have 2.80–3.96 times the odds. Even in the strictest comparison, within the same journal, year and primary topic, the lead-author odds ratio is 3.26 (95% confidence interval 2.32–4.59). These associations remain after accounting for prior citations, author geography and

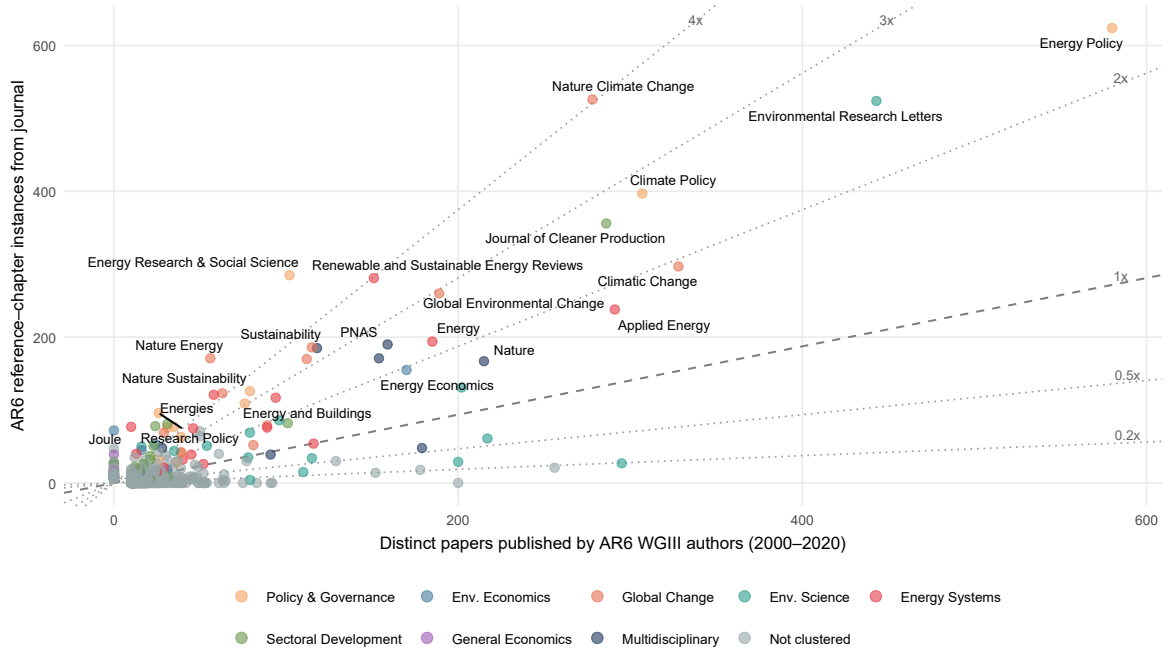


Figure 3: **Journals in the AR6 bibliography and in its authors' publication records.** Distinct papers published by matched AR6 WGIII authors during 2000–2020 (444 authors, 44,809 papers), against AR6 reference–chapter instances from each journal. The dashed line is the pooled instance-to-publication ratio, and dotted lines mark 0.2, 0.5, 2, 3 and 4 times that ratio. Journals with one to four author-published papers are omitted; cited journals in which no matched author published appear at zero. Colours denote journal clusters, as in Figure 2.

team characteristics.

4.2.2 Prior citations and geography

Prior scholarly attention is also strongly associated with selection: each doubling of one plus citations accumulated through 2017 is associated with 82–91% higher odds of inclusion, within journals and in the narrower subject comparisons. The assessment therefore draws disproportionately on papers that were already visible before its authors were appointed in January 2018.

Geography distinguishes selected papers within these comparisons as well: papers whose authors are all based in the Global South have 35–56% lower odds of inclusion than papers with Global North-only teams. The gap is largest for papers whose authors are all based in mainland China: their odds ratios range from 0.30 to 0.43. For other Global South-only papers, the odds ratio rises from 0.48 in the journal–year comparison to 0.81 in the exact-topic comparison, where its 95% interval includes one (0.61–1.08). The geographic pattern is therefore uneven, and the narrower sample does not support treating all Global South research as facing the same difference in inclusion.

Figure 4 shows the raw composition of the two samples, before any adjustment. Pooling publication years 2010–2021, teams based only in the Global South wrote 9.0% of the AR6-cited papers, compared with 20.3% of uncited papers sampled from the same journals and years. Global North-only teams wrote 76.3% and 63.5%, and mixed teams 14.7% and 16.2%. The gap

Table 2: Paper-level correlates of selection, with the AR6-author link split by role

	(1) Exact topic	(2) Exact subfield	(3) Journal–year
Prior citations (doubling of $1 + c$)	1.82*** [1.57, 2.11]	1.85*** [1.68, 2.03]	1.91*** [1.81, 2.03]
Global South only (ref.: Global North only)	0.65*** [0.52, 0.81]	0.45*** [0.35, 0.58]	0.44*** [0.37, 0.52]
Mixed Global North–South team	0.75 [0.51, 1.09]	0.64*** [0.49, 0.82]	0.73*** [0.62, 0.86]
International author team	1.05 [0.87, 1.28]	1.10 [0.95, 1.27]	1.01 [0.93, 1.10]
Number of authors (doubling of $1 + n$)	1.02 [0.84, 1.24]	0.93 [0.78, 1.12]	0.84*** [0.76, 0.93]
At least one appointed AR6 lead author (CLA or LA)	3.26*** [2.32, 4.59]	4.47*** [3.19, 6.27]	6.18*** [4.80, 7.95]
Other credited AR6 authors only	2.80** [1.51, 5.21]	3.15*** [2.08, 4.79]	3.96*** [3.10, 5.05]
Selected papers	696	1,303	3,370
Control papers	4,151	8,944	27,425
Choice sets	473	765	1,287
Journals	124	237	675
Choice-set fixed effects	Yes	Yes	Yes
Journal-clustered standard errors	Yes	Yes	Yes

Notes: Entries are conditional odds ratios with 95% confidence intervals in brackets. The dependent variable equals one when a paper is cited in AR6 WGIII. All comparisons are within publication journal and year; columns 1 and 2 additionally match on OpenAlex primary topic and subfield, respectively. Prior citations are accumulated through 2017, before the January 2018 author selection. Retained choice sets contain at least three controls per cited paper. Standard errors are clustered by journal. Appointed lead authors are Coordinating Lead Authors and Lead Authors. Other credited authors are Contributing Authors, Review Editors, chapter scientists, and editorial roles. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

widened over the period. Among the comparison papers, the Global South-only share rose from 11% in 2010 to 21–23% in 2017–2021; among cited papers it rose from 5% to 8–11%. These shares are unconditional. They do not adjust for topic, and part of the difference reflects the subjects on which Global South-only teams publish, as the weaker exact-topic estimate for papers outside mainland China indicates. Geography is classifiable for 95.3% of cited and 90.4% of comparison papers, and refers to the authors' institutional affiliations, rather than their nationality or the location studied in the paper. Section 5.3 compares these shares with the geography of the assessment's own authors.

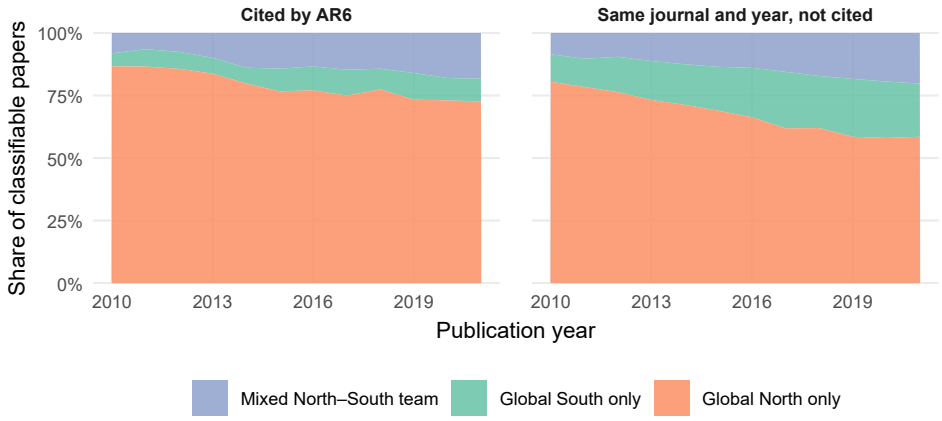


Figure 4: **Author-team geography of cited and comparison papers.** Annual author-team composition of AR6-cited papers and of uncited papers randomly sampled from the same journal–publication-year cells, 2010–2021, among papers with classifiable geography. These shares are unadjusted. Geography is based on authors' institutional affiliations.

The cross-sectional comparison therefore establishes alignment with the appointed authors,

among papers from the same journals and topics and after accounting for prior visibility and geography. In the next section, I ask whether the lead author bonus persists over successive reports.

4.3 Writing-team turnover

Both the experts and the evidence are largely renewed between reports. In the 14 matched chapters, 83% of AR6 appointed lead authors had not served on the predecessor chapter, and only 8.8% of AR5 works with a DOI are cited again in AR6, while 3.6% of AR6 works with a DOI had already appeared in AR5 (Supplementary Figure S4). The question is whether the two renewals are related.

4.3.1 Incoming and outgoing authors

Both groups were chosen as experts on the subject of their chapter, and both kept publishing over the period spanning the two reports (see Supplementary Figure S8). In the 14 matched AR6 chapters, 13.5% of the references name at least one member of the chapter's own writing team (overall, 22.7% of the references in AR6's 17 chapters name at least one member of its writing teams). If a stable body of prominent research were cited whoever wrote the report, their shares of the chapter's references would therefore change little. Instead, the two groups are more cited in the report they helped to write (Figure 5). In all 14 pairs of chapters in AR5 and AR6, the share of references naming at least one incoming author rose between AR5 and AR6 and the share naming at least one outgoing author fell; giving each pair equal weight, the first rose by 7.9 percentage points (95% chapter-pair interval 6.1–9.8) and the second fell by 7.5 points (6.5–8.6). Pooled over all references, outgoing authors appeared on 12.3% of AR5 references and incoming authors, not yet on the team, on 3.8%; in AR6, incoming authors appeared on 11.5% and outgoing authors on 4.0%. The two groups' ranking reversed in 13 of the 14 pairs, and in the remaining pair, AR6 Chapter 2 and its predecessor AR5 Chapter 5, incoming authors were already the more cited group in AR5 and their lead widened.

Adding the own-team gaps of the two bibliographies gives the two-cycle contrast, which averages 15.4 percentage points across pairs (13.3–17.6). Because the two groups differ in size, part of any gap could arise from size alone. Subtracting the mean gap under random reallocations of the authors to groups of the observed sizes changes the contrast little, to 15.2 points (13.1–17.4), because size favours incoming authors in both bibliographies and so works in opposite directions on the two gaps. The magnitude varies considerably between chapters, from 7.4 points in Buildings to 24.0 in Mitigation pathways, but the adjusted AR6 gap is positive in every pair (Figure 6). No single chapter drives the average, and weighting by the number of references leaves it little changed (Supplementary Table S5).

Contributing Authors join during drafting, and some may be invited because their work is already being assessed. Restricting both teams to the Coordinating Lead Authors and Lead Authors appointed before drafting removes this channel, and the shares then move mechanically by less but in the same directions in every pair: the incoming lead authors' share rises by 3.6 points on average (2.4–5.0) and the outgoing lead authors' share falls by 4.6 points (3.4–5.8), for a two-cycle contrast of 8.3 points (6.7–10.0), or 8.0 (6.5–9.7) after size adjustment, similarly

stable across chapters and specifications. The self-citation pattern does not depend on authors recruited after drafting began.

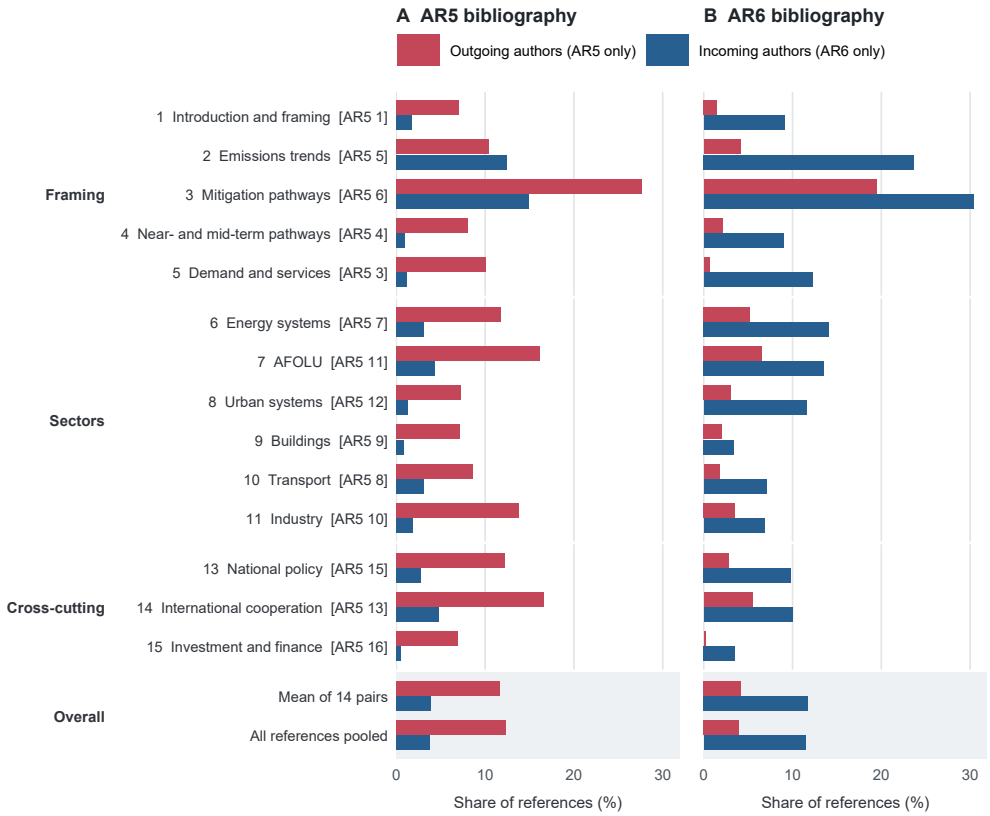


Figure 5: **Citation shares of outgoing and incoming authors in 14 matched chapter pairs.** Share of each chapter's references naming at least one outgoing author (serving on the AR5 chapter only; red) or incoming author (serving on the AR6 chapter only; blue), in the AR5 bibliography (A) and the AR6 bibliography (B). Authors are the whole credited writing team (Coordinating Lead Authors, Lead Authors and Contributing Authors), the main specification; the same shares by roles are in Supplementary Figure S5. The shaded rows average the 14 pairs with equal weights or pool all references.

4.3.2 Own vs. other chapters

If incoming authors were simply more citable in general, their advantage would appear across the whole report. Following the same authors into the bibliographies of the other matched chapters, which they did not write, holds the authors fixed, and there both groups are cited much less and with little difference between them. In the AR6 bibliography, incoming authors appear on 3.0% of the other chapters' references and outgoing authors on 1.7%, against 11.5% and 4.0% in their own chapter (Supplementary Table S6). For appointed lead authors the contrast is sharper: the two groups each appear on 0.9% of the other chapters' references, whereas in their own chapter incoming lead authors appear on twice as many references as outgoing ones (5.6% against 2.8%). After the size adjustment, the own-team gap is larger in the authors' own chapter than in the other chapters in every pair and in both cycles.

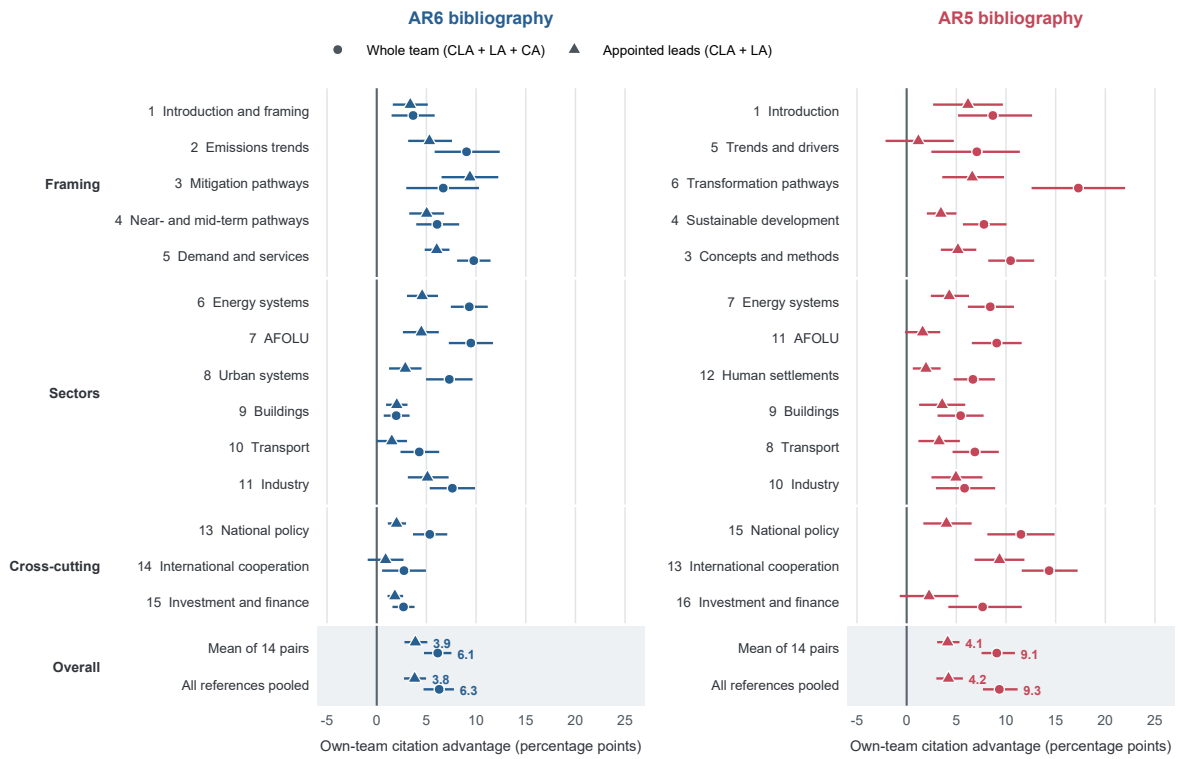


Figure 6: **Own-team citation advantage in each bibliography.** Share of references naming the team that wrote the bibliography minus the share naming the other team (AR6: incoming minus outgoing authors; AR5: outgoing minus incoming authors), after subtracting the mean gap under 9,999 size-preserving reallocations of authors within each pair. The two-cycle contrast is the sum of a pair's AR6 and AR5 values. Circles use the whole credited writing team, the main specification; triangles use appointed lead authors only. Chapter whiskers are solid 95% percentile intervals from resampling references within each chapter and bibliography; they describe citation-level variability for given rosters and chapters. In the shaded rows, the 14 pairs are averaged with equal weights or all references are pooled; their whiskers resample whole chapter pairs.

4.3.3 Global North and South authors

Most writing-team members are based in the Global North, so I repeat the turnover comparison separately within Global North and Global South author groups. This removes any general rise or fall in either group's visibility, but not changes that affected only the incoming authors. I find a positive adjusted contrast in all 14 chapter pairs for both groups (Supplementary Figure S6). The contrast is much larger in percentage points for Global North authors (12.5 versus 1.8), but Global South authors start from a far lower citation share. I cannot determine which group experienced the stronger proportional shift. The pattern is therefore consistent with writing-team alignment in both groups.

4.3.4 Older literature and research profiles

AR6 could cite publications that AR5 could not, and incoming authors may simply have produced more of that new work. Restricting both bibliographies to work published by 2013, before the AR5 literature cut-off date, preserves the direction of the pattern but reduces its size: the adjusted two-cycle contrast falls from 15.2 to 11.9 points (9.4–14.4) and remains positive in every pair. Most of what remains comes from the AR5 bibliography, consistent with the fact that

each report is encouraged to focus on the newest literature. In AR6, the writing team's gap on this older literature is 3.0 points (1.0–4.9) and positive in 10 of the 14 pairs, while for lead authors alone it cannot be distinguished from zero. The alignment is largest for most recent work (Supplementary Table S8). Even the older literature is largely reselected rather than inherited, since only 20.8% of AR6 references published by 2013 had been cited in AR5 (Supplementary Section S3.1).

I do not find differences in publication supply or research focus which could account for such a difference between citation patterns. Before 2014, outgoing authors published more than incoming authors (Supplementary Figure S8), yet on literature published by 2013 the AR6 bibliography names incoming authors more often. Incoming authors published more only from 2016, so for recent work supply and alignment cannot be separated. The incoming authors' research profiles are closer to those of the same chapter's outgoing authors than to the median other chapter's outgoing group in 13 of the 14 chapters for subfields and in all 14 for topics (Supplementary Section S3.9).

4.3.5 Comparison with non-writing experts

AR6 Coordinating Lead Authors and Lead Authors are cited more often in the chapters they write than in the other matched chapters, as their expertise would lead one to expect. To ask whether this concentration exceeds that of experts appointed for the same subjects, I compare it with that of the Coordinating Lead Authors and Lead Authors of the corresponding AR5 and AR7 chapters, excluding anyone who held a role in the AR6 chapter. The AR6 authors are cited eight times as often in their own chapter as in the other matched chapters (95% interval 6.4–10.3), against 3.5 and 3.4 times for their AR5 and AR7 counterparts (2.4–4.7 and 2.3–5.0).

Review Editors provide a second comparison: they are selected through the same process and appointed to the same chapters as the authors, but oversee the review rather than draft the text. Coordinating Lead Authors are the closest writing-role benchmark, since both positions are senior and are two or three per chapter (IPCC Working Group III, 2018). AR6 Coordinating Lead Authors are cited nine times as often in their own chapter as in the other matched chapters, against 2.0 to 2.9 times for the Review Editors of the AR5, AR6 and AR7 chapters and 2.6 and 4.7 times for the AR5 and AR7 Coordinating Lead Authors.

Because the ratio compares each group against itself, it does not depend on how often a group is cited overall. The AR6 authors are in fact cited somewhat more than the comparison groups in the other chapters (0.9% of references, against 0.6% and 0.4%) and much more in their own (7.3%, against 2.0% and 1.5%); the difference holds in every publication period (Supplementary Section S3.8).

5 Discussion and Conclusion

5.1 How the evidence relates to the experts

Earlier studies showed that the evidence reaching the IPCC and other intergovernmental bodies is concentrated among particular scientists and research communities (Jankó et al., 2017; Asatani et al., 2026; Hughes and Paterson, 2017; Gusheva et al., 2024), which could reflect a relatively

stable set of influential researchers whose work would be prominent whoever wrote the report. I show that experts on a chapter's subject are cited more in it whether or not they write it, but that the current writing team is cited most. Each chapter's research community thus contains two nested groups of influential authors, the experts on its subject and, within them, the team currently writing it.

Studies of evaluator proximity examine how experts judge the work submitted to them (Li, 2017; Teplitskiy et al., 2018; Tombazos and Dobra, 2014). In an assessment, the experts also choose which work to consider, and each chapter's bibliography shifts towards its writers' own research. This can happen because the writers' work is particularly relevant to the chapter, which is partly why they were appointed, or because writers give most attention to the work they know well, starting with their own (Ocasio, 1997). To distinguish the two, I compare the writers with experts appointed for the same subjects who did not write the chapter, and show that participation is driving most of the effect, without establishing favouritism or identifying which authors proposed particular citations.

Studies of journal editors and grant reviewers find that professional connections can improve research selection despite introducing preferential treatment (Laband and Piette, 1994; Brogaard et al., 2014; Li, 2017). A similar test in future research could compare the subsequent scientific uptake of author-linked and other IPCC-cited papers, conditional on their prior visibility, although later citations are an imperfect measure of quality and may themselves be influenced by IPCC inclusion. The findings show why both expert recruitment and evidence selection must be considered together. Assessment bodies need to use their authors' expertise while making sure that relevant research by others is also considered. Citing the authors' own work is not in itself inappropriate.

5.2 Scientific visibility, assessment uptake and research evaluation

In many disciplines, and in economics in particular, journal rank has become a main signal of research quality as hiring and promotion committees reward publications in top journals (Heckman and Moktan, 2020; Niles et al., 2020), which IPCC authors may replicate. Experimental evidence shows that adding publications in lower-ranked journals to an otherwise strong publication record can reduce assessments of a researcher's scientific contribution (Powdthavee et al., 2018; Hayes, 1983). Journal-based indicators can also misjudge the research they are meant to reward: novel papers are less likely to be highly cited within short citation windows and tend to appear in journals with lower-than-expected impact factors (Wang et al., 2017). Greater representation of prestigious journals could reflect either assessment authors using journal reputation as a signal of scientific quality or these journals publishing research that is, on average, more rigorous or relevant. Conversely, the disproportionate representation of specialist journals in the IPCC may be because of their closer topical fit, irrespective of prestige.

Prior visibility is itself strongly associated with inclusion in the IPCC. Within the same journal and publication year, already well-cited papers have substantially higher odds of being assessed, consistent with cumulative advantage in scientific attention (Merton, 1968; Price, 1976), although prior citations may also signal relevance or quality, and publication in higher-impact journals can itself increase a paper's scholarly visibility (Larivière and Gingras, 2010). Assessment citations may therefore partly reproduce existing patterns of recognition, and do not represent

an independent measure of research impact.

Citations in policy documents are increasingly used to measure the societal impact of research (Bornmann et al., 2016; Szomszor and Adie, 2022), and IPCC assessments are an early step through which research reaches those documents (Bornmann et al., 2022). The IPCC bibliographies show the direct influence of an article, but the secondary-reference analysis shows that some research is connected to an assessment without appearing in its bibliography. Some of the difference between primary and secondary citation can be explained by the writing team self-citation bias of the IPCC chapters. Therefore, future research should distinguish formal citation from substantive use as Distel et al. (2026) do for policy documents. Overall, assessment citations can provide valuable evidence of research policy use. However, replacing journal rankings with assessment citation counts alone would risk replacing one context-dependent indicator with another.

5.3 Implications for assessment practice

The findings reinforce the argument for balancing expertise in assessment teams. The IPCC already considers scientific perspectives, geography, gender and prior assessment experience when selecting authors (IPCC, 2012), but its bibliography still shows uneven geographical inclusion: 37.0% of AR6's appointed lead authors list affiliations only in the Global South, whereas teams based only in the Global South wrote 9.0% of the cited papers in the sampled journals, against 20.3% of comparable uncited papers. I find no significant difference in self-citation for Global South and Global North authors in the IPCC, which suggests that expanding the geographic coverage of the authors' team would also expand the reviewed literature. More generally, the renewal and expansion of the writing team of an expert panel might increase the diversity of coverage especially if the authors' work, which is likely to get cited, is complementary.

The relationship between experts and evidence also bears on debates about industry participation. Historical research documents involvement in IPCC mitigation assessments by experts affiliated with fossil-fuel companies and petroleum industry associations (Fressoz, 2025). A recent journalistic investigation raises concerns about potential conflicts among AR7 authors with fossil-fuel ties (Carrington et al., 2026). The present analysis neither evaluates these cases nor establishes that commercial interests explain bibliographic alignment, my point is that these debates should also consider who assembles the evidence. The IPCC's conflict-of-interest policy distinguishes scientific perspectives, which can be balanced through team composition, from interests requiring disclosure and management (IPCC, 2016). This distinction matters for all expert assessment panels that draw on knowledge from sectors whose activities they assess.

The IPCC already subjects its reports to extensive review, yet the resulting bibliographies remain associated with the teams responsible for drafting. The IPCC's reviewers are named at the report level and I cannot perform a self-citation analysis for this category, or show that it helped increase the coverage of the report. However, in theory, reviewers who know relevant literatures less familiar to the writing team could flag studies the chapter has missed. Finally, providing structured chapter bibliographies, linked to author roles and affiliations, would make such scrutiny easier and allow independent examination across assessment cycles. For this study I had to rebuild them from the report PDFs and could not recover 100% of the references, which illustrates the practical importance of making the bibliography readily usable.

These findings also apply to literature reviews done by artificial intelligence or other tools,

which are already used to map climate research at scale (Callaghan et al., 2020). Tools that rely heavily on prior citations risk reproducing existing differences in visibility, which I find strongly predicts inclusion. Retrieval software should therefore also be evaluated on their ability to identify relevant research absent from previous assessments (Ford et al., 2025). Automation offers an opportunity to extend the literature available to experts. However, future research must assess whether it truly increases assessment coverage. Removing the experts would not remove selection, but would leave it to black-box for-profit models.

Data availability

Processed datasets and replication code will be available upon acceptance and will be deposited in a public repository on publication. The IPCC reports are publicly available at https://www.ipcc.ch/reports/.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the author used Claude (Anthropic) and Codex (OpenAI) to edit and restructure the text and check its consistency with the results. After using these tools, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

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Supplementary material for "Which science reaches the IPCC? Expert recruitment and evidence selection"

This supplement is organised in five sections. Section S1 describes the data and methods: reference extraction, journal matching and classification, author bibliographies, the paper-level comparison sets and the turnover estimator. Section S2 reports the journal-level results in more detail, covering journal prestige, secondary references and the authors' publication venues. Section S3 covers the writing-team comparison: how many references carry over between reports, chapter-level estimates and their sensitivity, and the identification checks (own versus other chapters, Global North and Global South authors, literature of the same age, concentration in the matched chapter, and the publication records of incoming and outgoing authors). Section S4 gives the full paper-level selection models and their robustness checks, and Section S5 lists the journal abbreviations.

S1 Data and methods **S2**
- S1.1 Data Sources . . . S2
- S1.2 Reference extraction from IPCC assessment reports . . . S2
- S1.3 Metadata of references . . . S3
  - S1.3.1 API and metadata providers . . . S3
  - S1.3.2 Journal matching . . . S4
- S1.4 Journal quality and disciplinary classification . . . S4
- S1.5 Journal clusters . . . S5
- S1.6 Climate-relevant output classification . . . S6
- S1.7 Author publication footprints . . . S7
- S1.8 Paper-level selection within journal–year opportunity sets . . . S8
- S1.9 Chapter-roster turnover and cross-chapter placebo . . . S9
- S1.10 Turnover estimator . . . S12
- S1.11 Global North and Global South authors . . . S12

S2 Journal prestige, secondary references and author footprints **S14**
- S2.1 Journal prestige and selection intensity . . . S14
- S2.2 Author publication footprints and geography . . . S15
- S2.3 Journal communities across chapters . . . S15

S3 Reference persistence, turnover estimator and chapter-level results **S18**
- S3.1 Persistence of references between assessment cycles . . . S18
- S3.2 Chapter-level estimates and sensitivity . . . S18
- S3.3 Continuing authors and appointment roles . . . S19
- S3.4 Own chapter and other matched chapters . . . S19
- S3.5 References close to the chapter outline . . . S21
- S3.6 Global North and Global South authors . . . S21
- S3.7 Literature of the same age . . . S22
- S3.8 Concentration in the matched chapter . . . S24
- S3.9 Publication records of incomers and exiters . . . S25

S4 Paper-level selection models **S30**
- S4.1 Robustness: papers published after author selection . . . S32

S5 Journal abbreviations **S34**

S1 Data and methods

Although structured reference lists are not provided, each chapter of each report contains a reference list at the end. I 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.

S1.1 Data Sources

I study the references cited in the Working Group III contributions to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (AR6), published in 2022, and to the Fifth Assessment Report (AR5), published in 2014.

Both reports, and the earlier ones, are publicly available at https://www.ipcc.ch/reports/.

For the AR5 and AR6 WGIII chapter bibliographies used here, I retrieved the official report PDFs and did not find a complete structured export covering both reports at the time of extraction.

S1.2 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 practice and software between the two reports, 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.
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

of 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 18,047 reference instances, corresponding to 15,643 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 arise 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 *available upon acceptance.*

S1.3 Metadata of references

S1.3.1 API and metadata providers

I retrieved journal, author, DOI, citation-history, and reference-list metadata through the OpenAlex and Scopus APIs in R. Requests complied with the providers' rate limits and terms of service.

OpenAlex. OpenAlex is an open and continuously updated graph of scholarly works, authors, institutions, venues, topics, references, and citations (Priem et al., 2022). I used it to match AR6 references and to obtain work-level metadata, reference links, topics, authorships, and annual citation counts. Its coverage is not exhaustive and historical reference links vary across publishers and publication years. OpenAlex indexes works published before 2012, but the annual-count field used here is not consistently available before 2012. The paper-level cohort therefore begins in 2012 so that prior citations can be measured on a common basis through 2017. Fresh API checks on a random sample reproduced the cached pre-2018 counts closely.

S1.3.2 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.

Two external abbreviation catalogues underpin the normalisation: the Web of Science journal-title abbreviation lists[3], and the University of British Columbia's journal-abbreviation database[4] (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 is 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 as 10.1111/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.

S1.4 Journal quality and disciplinary classification

To assign each outlet a quality tier, I use SCImago Journal Rank (*SJR*). It provides a prestige-weighted citation score and subject-category quartile for Scopus-indexed titles. Main-text Figure 1, Figure S2 and Section S2.1 use the 2021 score.

SJR is a size-independent, PageRank-like indicator: citations transfer more weight when they originate in journals with greater standing, and the resulting journal prestige is divided by the journal's recent article output. The measure therefore captures prestige-weighted citation influence per article rather than publication volume or an expert-panel tier. The Scopus-wide weighted mean is one, but the score is strongly right-skewed. I obtained annual scores from Elsevier's official SciVal SJR workbook for 2010–2021, from the SciVal metric documentation

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

page[5]. The workbook identifies journals by Scopus Source ID and supplies year, subject category, SJR, quartile and percentile. I selected year 2021, retained one identical SJR value per Source ID when a journal occurred in multiple subject categories, and joined Source IDs through the 2024 SCImago source file already used in the journal pipeline. The title crosswalk includes the explicit SCImago title *Sustainability (Switzerland)* for *Sustainability*. All 35 journals displayed in main-text Figure 1 match to a 2021 score.

The colour bins are fixed doublings of the raw score: grey for SJR < 1, blue for $1 \leq$ SJR < 2, light blue for $2 \leq$ SJR < 4, orange for $4 \leq$ SJR < 8, and red for SJR ≥ 8. These thresholds are independent of the 35-journal display and preserve large differences within the upper tail that percentile categories compress. They are not SJR subject-category quartiles. All association tests use the unbinned score and are reported for the 146 journals with at least ten cited works across the two reports and with output and SJR data in Section S2.1.

I combine it to four more journal classification sources: the CNRS Section 37 list (2022), the London School of Economics departmental rankings (2024), the SCImago Journal Rank (2024), and the RePEc journal roster (June 2025). A journal is classified as "Economics" if it appears in either the CNRS list or the RePEc roster, including multidisciplinary outlets.

S1.5 Journal clusters

Individual IPCC chapters do not draw uniformly from the climate literature. To describe which disciplinary communities each chapter draws on (main-text Figures 2 and 3 and Figure S3), I group 90 outlets into epistemic clusters defined by their dominant disciplinary and topical orientation: the 52 most-cited outlets, plus 38 further journals labelled in main-text Figure 2 (listed after "Also" in Table S1). The assignment was made by hand from each journal's stated aims and scope; for the 52 most-cited outlets it was checked against an automated clustering of the same scope texts. Journals outside this list are shown as "Not clustered". The clusters are descriptive and are not used in any estimate.

[5] https://www.elsevier.support/scival/answer/scival-metric-sjr

Table S1: **Journal clusters.** Members of each descriptive cluster used in main-text Figures 2 and 3 and Figure S3.

Cluster	Journals
Global Change	Nature Climate Change; Climatic Change; Global Environmental Change; Nature Energy; Nature Sustainability; Sustainability; Ecological Economics. *Also:* Annual Review of Environment and Resources; Current Opinion in Environmental Sustainability; Mitigation and Adaptation Strategies for Global Change; Sustainability Science
Multidisciplinary	Proceedings of the National Academy of Sciences; Nature Communications; Science; Nature. *Also:* One Earth; PLOS ONE; Scientific Reports
Env. Science	Environmental Science & Technology; Science of the Total Environment; Journal of Environmental Management; Environmental Research Letters. *Also:* Atmospheric Chemistry and Physics; Atmospheric Environment; Earth System Science Data; Energy & Environmental Science; Geophysical Research Letters; Global Biogeochemical Cycles; Global Change Biology; Nature Geoscience; Resources, Conservation and Recycling
Policy & Governance	Environmental Science & Policy; Energy Policy; Climate Policy; Energy Research & Social Science; Technological Forecasting and Social Change; Research Policy; Environmental Politics; International Environmental Agreements: Politics, Law and Economics; Journal of Environmental Planning and Management. *Also:* Ecology and Society; Environmental Innovation and Societal Transitions; Global Environmental Politics; Journal of Environmental Psychology
Energy Systems	Applied Energy; Energy; Energy and Buildings; Energies; Renewable Energy; Renewable and Sustainable Energy Reviews; Energy Journal. *Also:* Biomass and Bioenergy; Energy Conversion and Management; Energy Efficiency; Energy Procedia; International Journal of Greenhouse Gas Control; International Journal of Hydrogen Energy; Joule; Journal of Power Sources; Solar Energy
Sectoral Development	Journal of Industrial Ecology; Journal of Cleaner Production; World Development; Food Policy; Transport Policy; Transport Reviews; Urban Studies. *Also:* Agriculture, Ecosystems & Environment; Building and Environment; Global Food Security; Sustainable Cities and Society; Transportation Research Part A; Transportation Research Part D; Waste Management
Env. Economics	Energy Economics; Resource and Energy Economics; Journal of Environmental Economics and Management; Environmental and Resource Economics; Review of Environmental Economics and Policy; Climate Change Economics
General Economics	American Economic Review; European Economic Review; Journal of Economic Perspectives; Journal of Public Economics; Journal of Political Economy; Quarterly Journal of Economics; Econometrica; Review of Economic Studies. *Also:* Journal of Economic Literature; Management Science

S1.6 Climate-relevant output classification

To normalise citation counts by the climate-relevant output of generalist journals, I classify 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 estimate each journal's climate share on the same items as its output denominator: papers published during 2005–2021, excluding errata, book reviews and other non-research items (and, for *Nature* and *Science*, items without references). For each journal I draw a random sample of up to 800 such papers with a fixed seed; journals with fewer papers are covered in full. The share is computed among papers with at least one OpenAlex topic, and its standard error is at most two percentage points for every journal. Shares are available for the 30 journals most cited in the IPCC and the 25 most-cited economics journals, 50 of which are in the journal comparison. As the IPCC WGIII is focused on climate-change mitigation, I do not include keywords such as "Biodiversity" or damages-related terms (e.g. flood, heatwave), as these pertain respectively to IPBES and IPCC Working Group II.

Over 2005–2021, generalist journals have climate-related shares of about 6–12%: *Nature* (9.9%), *Science* (12.4%) and *PNAS* (6.5%), and among the general-interest economics journals the *American Economic Review* (8.9%), the *Quarterly Journal of Economics* (8.7%) and the

Journal of Political Economy (9.4%). Specialised journals have much higher shares, above 80%: *Energy Policy* (97%), *Energy Economics* (85%), the *Journal of Environmental Economics and Management* (82%) and *Ecological Economics* (80%). Shares measured on papers published in a single year are close to these for specialised journals but can differ substantially for generalist ones (Figure S1); the *Journal of Political Economy*, for example, has 10.8% in 2017 and 2.3% in 2024. Using the 2017 or 2024 shares instead of the 2005–2021 sample gives climate-adjusted correlations with SJR of 0.41 and 0.38 (Section S2.1).

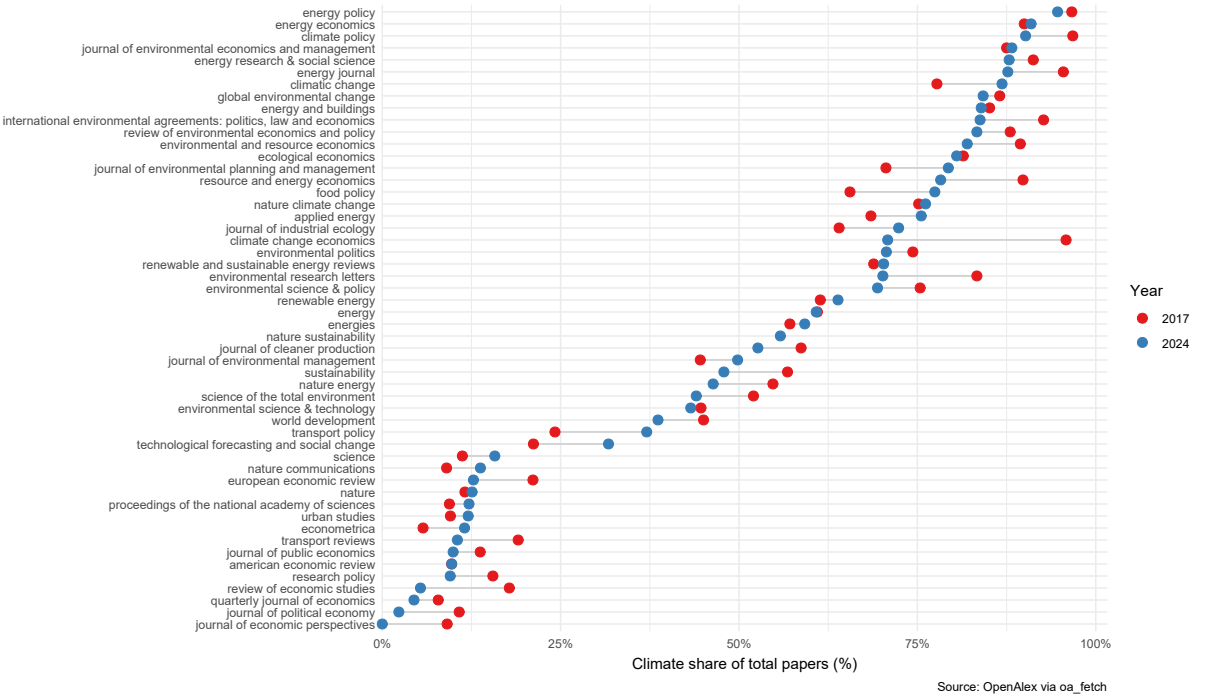


Figure S1: **Share of climate-related papers by journal, 2017 and 2024.** Share of each journal's output in each year classified as climate-related using the OpenAlex topic-keyword rule described above. The journal comparisons use shares estimated on 2005–2021 output instead.

S1.7 Author publication footprints

To characterise the publication venues in which IPCC authors are active, I constructed journal-level publication footprints for all authors contributing to the IPCC Sixth Assessment Report Working Group III (WGIII). I compiled a list of 483 Coordinating Lead Authors, Lead Authors, Drafting authors, and Contributing Authors from the chapter-level authors printed in the reports. For each individual, I queried the OpenAlex database for all scholarly works published between 2000 and 2020.

Author retrieval was performed using the OpenAlex author search endpoint, combining name-based queries with manual validation. Automated author search frequently returned homonymous or highly cited authors with identical names; all author profiles were therefore automatically disambiguated using IPCC-related published works to select the most likely candidate.

For each of the 444 validated authors, I retrieved all associated works published within the study window, yielding 44,809 total publication records. For each paper, journal metadata were extracted using OpenAlex venue identifiers. Journal names were normalised to canonical full titles to ensure consistency across records. Publications were aggregated at the journal level in two ways: distinct OpenAlex works and author–paper pairs, with a coauthored work counted once for each matched IPCC author.

To enable comparison with IPCC citation patterns, journal-level publication footprints were subsequently merged with journal-level citation counts derived from the IPCC WGIII reference

lists. Journals with one to four author-published papers over the study period are omitted from main-text Figure 3 to reduce noise from sparsely represented venues; cited journals in which no matched author published are shown at zero. The resulting dataset allows testing whether journals that IPCC authors publish in more frequently are also cited more intensively in the assessment, and whether certain journals are cited disproportionately relative to author publication volume.

Several limitations should be noted. Publication footprints capture venue frequency rather than the substantive influence of individual papers, and manual author disambiguation, while conservative, may undercount publications for authors with fragmented OpenAlex profiles. I therefore complement this aggregate analysis with a separate paper-level design.

S1.8 Paper-level selection within journal–year opportunity sets

The paper-level analysis asks which observable characteristics distinguish AR6-cited papers from papers that were available in the same publication venues. The cohort is restricted to 2012–2017 so that every paper and its measured prior visibility predate selection of the AR6 author team in January 2018. This design cutoff is distinct from the AR6 WGIII cutoff for accepted papers, 11 October 2021. Cited papers require a DOI, journal, and publication year; the legacy treated-work cache does not retain a separate OpenAlex type field. Controls are OpenAlex articles and reviews not cited by AR6, randomly drawn with a fixed seed from the same journal–year cell at a target of ten controls per cited paper. The sampling endpoint is used rather than citation-ordered result pages. Duplicate DOIs, DOIs assigned to conflicting journal–year cells, and controls that appear in the AR6 bibliography are removed. For a work-type robustness check, I separately retrieved the OpenAlex type of every treated DOI and restricted both treated and control works to articles and reviews. When OpenAlex returned duplicate records for a DOI, I selected the record with the largest current cited-by count, using the OpenAlex identifier as a deterministic tie-break; the exact locally cached work record took precedence where available. Types were resolved for 3,939 of 4,036 treated DOIs: 3,868 were articles or reviews, 71 had another type, and 97 unresolved records were excluded from this check.

For each paper, prior scientific visibility is measured as $\log_2(1 + c)$, where c is the number of citations accumulated through 2017. A one-unit coefficient therefore describes a doubling of one plus citations.

Geographical affiliations Author affiliations classify papers as Global North-only, Global South-only, or mixed North–South. Countries are assigned using the list of Global South and Global North countries published by NORRAG, the Global Education Centre of the Geneva Graduate Institute (2023 list), matched to ISO 3166 country codes; it classifies 175 countries as Global South and 34 as Global North. "We understand “Global South” to refer both to a geographical location and a political subjectivity born from the lateral solidarities among the world’s multiple Souths (Mahler, 2017)[6]." Under this list, for example, China, India, Brazil, Mexico, South Africa, Türkiye, Singapore, and the Gulf states are Global South, whereas the United States, Canada, the United Kingdom, Japan, the Republic of Korea, Israel, Australia, and most European Union member states are Global North. The NORRAG list is unusual in placing several European countries in the Global South, including Russia, Ukraine, Belarus, Czechia, Slovakia, Romania, Bulgaria, Croatia, Cyprus, and Malta. As a robustness check, I re-estimated the paper-level models with UNCTAD’s developed/developing grouping, although it does not describe the same power dynamic, which places Europe, Northern America, Israel, Japan, the Republic of Korea, Australia, and New Zealand in the North and differs from the NORRAG list for 16 European countries (Cyprus, located in Western Asia, remains in the Global South). On identical samples, the alternative classification changes the category of 1–2% of papers (8, 16, and

[6] https://www.norrageducation.org/surface-under-represented-expertise/, Reference Mahler (2017)

24 cited papers in the topic-, subfield-, and journal–year-matched samples) and leaves the Global South-only odds ratios essentially unchanged: 0.63 [0.51, 0.78], 0.44 [0.35, 0.56], and 0.45 [0.38, 0.54], compared with 0.65, 0.45, and 0.44 in the main specification. Additional covariates indicate whether authors are based in more than one country, $\log_2(1 + a)$ for a authors, and whether any coauthor appears on the final credited AR6 WGIII roster. A supplementary specification splits this indicator into two mutually exclusive indicators: at least one appointed lead author (Coordinating Lead Author or Lead Author; 225 of the 444 credited OpenAlex profiles), or only other credited roles. Publication-time affiliations are used where available; missing countries are not inferred from current profiles. The full models use complete cases for citation history, geography, author count, and roster linkage. Papers with partially or wholly missing affiliation countries are excluded from those models, and no missing value is coded as Global North.

I estimate conditional-logit models in three nested samples. For paper i in choice set s,

$$\log\left[\frac{\Pr(Y_{is} = 1)}{1 - \Pr(Y_{is} = 1)}\right] = \alpha_s + \boldsymbol{x}'_{is}\boldsymbol{\beta},$$

where $Y_{is} = 1$ denotes AR6 inclusion and α_s is conditioned out. The strictest choice sets require the same journal, publication year, and OpenAlex primary topic; a broader specification requires the same journal, year, and subfield; and the broadest requires the same journal and year. Each retained choice set contains at least one cited paper and at least three controls per cited paper. Standard errors are clustered by journal, allowing arbitrary dependence among papers assigned to the same journal. Because controls are sampled retrospectively, odds ratios compare characteristics within sampled opportunity sets and are not population inclusion probabilities. The reported intervals condition on the realised control draw; a separate 20-draw control-resampling check evaluates sensitivity to that draw.

The exact-topic specification retains 696 cited papers, 4,151 controls, 473 choice sets, and 124 journals. It is unusually concentrated in *Energy Policy*, which contributes 20% of cited papers, because many journal–year–topic cells do not contain enough sampled controls after complete-case restrictions. I therefore use this model as a stringent but selective comparison. The exact-subfield specification retains 1,303 cited papers, and the journal–year specification retains 3,370 cited papers—83% of the 4,042 eligible cited-paper cohort—across 675 journals. The three estimates triangulate the same question but use different samples. I therefore also re-estimate all three strata definitions on their common support of 4,833 papers (693 cited and 4,140 controls); Fig. S11 reports this comparison. The replication output also reports retained and excluded distributions by geography, roster link, year, work type where recorded, and journal. Requiring 1, 3, 5, or 10 controls per cited paper leaves the visibility and author-link associations positive throughout. Global South-only point estimates remain below one, although their intervals include one at thresholds of 5 and 10 as the retained sample becomes sparse.

A supplementary heterogeneity specification divides Global South-only papers into those whose authors are all affiliated with institutions in mainland China and those from other Global South countries. Hong Kong, Macao, and Taiwan are not included in the mainland China category. These models use exactly the same samples as the corresponding aggregate-geography models, so differences reflect the alternative geography coding rather than sample changes.

S1.9 Chapter-roster turnover and cross-chapter placebo

Chapters matching I use a hand-checked conceptual crosswalk to pair 14 AR6 chapters with direct AR5 predecessors (Table S2) . AR6 Chapter 3 is paired with AR5 Chapter 6, which covers transformation pathways. AR5 Chapters 2 (Integrated risk and uncertainty assessment of climate change response policies) and 14 (Regional development and cooperation), AR6 Chapters 12 (Cross-sectoral perspectives), 16 (Innovation, technology development and transfer), and 17 (Accelerating the transition in the context of sustainable development), and AR7 Chapters

4 (Sustainable development and mitigation), 5 (Enablers and barriers), 14 (Integration and interactions across sectors and systems), and 15 (Potentials, limits, and risks of carbon dioxide removal) have no clear counterpart and are not used.

Table S2: **Chapter crosswalk across AR5, AR6, and AR7 (WGIII).** Each row gives the chapter number and official title in each cycle, ordered by AR6 chapter. Daggers mark the three AR5–AR6 pairs whose chapters differ in scope; they are left out in the crosswalk sensitivity of Table S5.

AR5 (2014)	AR6 (2022)	AR7 (in preparation)
1 Introductory chapter	1† Introduction and framing	1 Introduction and framing
5 Drivers, trends and mitigation	2 Emissions trends and drivers	2 Past and current anthropogenic emissions and their drivers
6 Assessing transformation pathways	3 Mitigation pathways compatible with long-term goals	3 Projected futures in the context of sustainable development and climate change
4 Sustainable development and equity	4† Mitigation and development pathways in the near- to mid-term	3 Projected futures in the context of sustainable development and climate change
3 Social, economic and ethical concepts and methods	5† Demand, services and social aspects of mitigation	8 Services and demand
7 Energy systems	6 Energy systems	9 Energy systems
11 Agriculture, forestry and other land use (AFOLU)	7 Agriculture, forestry, and other land uses (AFOLU)	13 Agriculture, forestry, and other land uses (AFOLU)
12 Human settlements, infrastructure and spatial planning	8 Urban systems and other settlements	12 Buildings and human settlements
9 Buildings	9 Buildings	12 Buildings and human settlements
8 Transport	10 Transport	11 Transport and mobility services and systems
10 Industry	11 Industry	10 Industry
15 National and sub-national policies and institutions	13 National and sub-national policies and institutions	6 Policies and governance and international cooperation
13 International cooperation: agreements and instruments	14 International cooperation	6 Policies and governance and international cooperation
16 Cross-cutting investment and finance issues	15 Investment and finance	7 Finance

IPCC authors The primary roster includes Coordinating Lead Authors (CLA), Lead Authors (LA) and Contributing Authors (CA), excluding drafting authors, review editors, and assistants credited later or in other functions. As a robustness check, I restrict the set of authors to CLA and LA only, which are appointed by the IPCC bureau. Lead authors are classified as continuing, entering, or exiting across each matched pair. Roster names and parsed reference authors are normalised to a surname–first-initial key. I audited every key assigned to multiple roster full names: spelling, diacritic, particle, and expanded-initial variants were retained, while six keys that conflate distinct people were excluded from rosters and references. The analysis records a direct author match only. Using one key per person avoids double-counting aliases but cannot eliminate every homonym or change in published name. I validated the keys against OpenAlex author identifiers for cited works with a DOI published in 2000–2020: the keys recover 97–98% of the links found through identifiers, and 98–99% of AR6 key matches are not homonyms, that is, not a different person with the same surname and first initial. Table S3 collects these and the other validation checks by stage of the data construction.

Turnover analysis For each AR6 reference–chapter pair, I recorded whether at least one reference author belonged to each roster group. The size benchmark pools entering and exiting

Table S3: **Validation of the bibliographic and author data, by stage.**

Stage	Check	Result
Reference extraction	Parsed reference counts compared with manual counts for the first chapter; visual inspection of the parsed output	Parsing rules validated on that chapter; several dozen manual corrections (over-long strings, duplicate DOIs)
Author names in references	Share of matched reference–chapter pairs with at least one usable surname–initial key	AR5: 91.2% after a cycle-specific re-parsing (63.7% with the generic parser); AR6: 99.2%. Turnover shares computed only over keyed references: Table S5
Roster keys	Every key shared by several roster full names audited by hand	38 keys audited; 32 retained as variants of one name, 6 conflating distinct people excluded from rosters and references
Key matches	Keys compared with OpenAlex author identifiers for cited works with a DOI published in 2000–2020	Keys recover 97–98% of identifier links; 98–99% of AR6 key matches are not homonyms
Work identifiers	DOI normalisation and pattern validation	4,594 of 8,806 distinct AR5 works (52%) and 11,199 of 15,643 AR6 works (72%) have a valid DOI
Journals	Normalisation against two abbreviation catalogues, then OpenAlex look-up by DOI	5,107 distinct AR5 works and 10,905 AR6 works assigned to a recognised journal
Author publication records	OpenAlex author search, disambiguated against each author's IPCC-related works	444 of 483 credited AR6 authors; 352 incomers and 306 exiters profiled for the turnover comparisons

authors within a matched chapter and reallocates them to two synthetic rosters of the observed sizes 9,999 times, holding the observed reference–author links fixed. This benchmark accounts for unequal roster sizes; it does not model the appointment process or control authors' scientific prominence. Pooled summaries give each chapter pair equal weight, and their intervals resample whole chapter pairs (Section S1.10).

The specificity test applies each chapter's entering and exiting roster to the bibliography of its own AR6 chapter and to the other matched chapters. Its random-allocation expectation is computed exactly from the pooled roster size and the number of roster-linked authors on each reference. Pooled estimates for this test weight chapter contrasts by their numbers of reference–chapter pairs, so the estimand is the average reference-level contrast rather than the average chapter. I describe uncertainty in the own-minus-other contrast by resampling the 14 matched rosters with replacement. Because these chapters are not a random sample, the interval shows how sensitive the estimate is to individual chapters, and should not be read as inference about other chapters.

The two-cycle check applies the same roster partition to each matched AR5 predecessor bibliography. Because AR5 and AR6 use different reference formats, AR5 author strings are parsed with a cycle-specific routine before applying the same surname–first-initial keys. A usable author key is recovered for 91.2% of the 8,101 AR5 reference–chapter pairs and 99.2% of the 14,138 AR6 pairs. Each size-preserving roster relabelling is applied jointly to the two bibliographies, and the two-cycle statistic subtracts the AR5 entrant–exiter gap from the AR6 gap. The primary summary gives each chapter pair equal weight (15.2 percentage points for the whole team, 8.0 for lead authors). Weighting each cycle by its own reference counts gives 15.6 and 8.0, and common weights based on the minimum, harmonic mean, or mean of the two reference counts give between 15.6 and 15.9 for the whole team (8.0 and 8.2 for lead authors). The primary specification includes Coordinating Lead Authors, Lead Authors, and Contributing Authors. A restricted specification excludes Contributing Authors, who are recruited during drafting.

I additionally test whether the roster result survives restriction to papers independently classified as relevant to the citing chapter. Paper text combines abstracts with OpenAlex concepts; chapter text comes from the WGIII outline adopted in September 2017, before author selection. Papers and the 17 outline chapters are represented in one TF–IDF space and compared by cosine similarity. This timing avoids using the completed assessment or its bibliography to assign topics. The actual citing chapter is the highest-scoring chapter for 29.3% of subsequently cited papers and appears among the three highest-scoring chapters for 52.5%. Because classification performance varies across chapters, these scores are used only for sensitivity restrictions, not to replace observed chapter identities or as an instrument.

S1.10 Turnover estimator

This section completes the description in main-text Section 3.3. For each matched chapter pair c, let S_c^5 and S_c^6 be the AR5 and AR6 rosters, either the whole credited writing team (CLA, LA, CA; primary) or the appointed lead authors (CLA, LA). Entrants are $E_c = S_c^6 \setminus S_c^5$ and exiters $X_c = S_c^5 \setminus S_c^6$; continuing authors are left out. (The main text calls them incoming and outgoing authors.) Let $s_c^k(A)$ be the share of the N_c^k references of chapter c in report k that name at least one member of A. With the own-team gaps D_c^5 and D_c^6 of the main text, the two-cycle contrast is

$$D_c^5 + D_c^6 = [s_c^6(E_c) - s_c^5(E_c)] - [s_c^6(X_c) - s_c^5(X_c)],$$

the entrants' change in share minus the exiters'. Both changes are reported, because their difference alone does not show whether both groups moved.

Size benchmark. In each of $B = 9{,}999$ draws, I relabel $|E_c|$ of the authors in $E_c \cup X_c$ as entrants and the rest as exiters, apply the same relabelling to both bibliographies and recompute the gaps $D_c^{k(b)}$. The adjusted gap is

$$\hat{\tau}_c^k = D_c^k - \frac{1}{B}\sum_{b=1}^{B} D_c^{k(b)}.$$

The benchmark absorbs differences in group size and in how often the pooled authors appear in the chapter's literature; it does not model the appointment process. For the whole team, entrants are the larger group (460 against 375 chapter memberships), so the benchmark lowers the AR6 gap and raises the AR5 gap. For lead authors, exiters are the larger group (179 against 136) and the corrections reverse. Because the correction has opposite signs in the two bibliographies, it nearly cancels in the two-cycle contrast.

Summaries and intervals. Primary summaries give each pair equal weight. Complementary summaries weight chapters by their references, $w_c^k = N_c^k / \sum_j N_j^k$, within each bibliography; because the AR5 and AR6 weights differ, the reference-weighted contrast is not an average of within-pair contrasts. Pooled intervals resample the 14 pairs with replacement (49,999 draws), keeping both bibliographies and both groups of a pair together and holding each pair's benchmark at its observed value. Chapter intervals resample references within each chapter and bibliography (9,999 draws); since each reference names an entrant only, an exiter only, both or neither, each draw is multinomial over these four cells. The main text states what these intervals do and do not describe.

S1.11 Global North and Global South authors

Most members of the writing teams are based in the Global North, so the turnover result could reflect a shift in the visibility of Global North researchers between the two assessments rather

than alignment with the team as such. This check repeats the turnover comparison separately within each geography, so that Global South entrants are compared only with Global South exiters, and Global North entrants only with Global North exiters. A change between AR5 and AR6 that raises or lowers the citation of all Global South (or all Global North) authors alike then cancels in the two-cycle contrast. A change specific to the Global South authors who joined the teams does not.

Author geography. Each author is classified from the countries listed in the chapter credits of the report in which they served on the pair: AR6 credits for entrants, AR5 credits for exiters. The AR5 credits list countries in the same format as the AR6 credits, and I parse them from the credit pages. Countries are classified with the NORRAG list used for the cited papers (Section S1.8). An author is Global South (North) if every listed country is Global South (North), and mixed otherwise. The few organisations listed in place of a country are assigned to their host country (IIASA and IAEA to Austria, FAO to Italy, and "European Union" in AR6 to Belgium), all of which are Global North. For the whole writing team, this gives 309 Global North, 106 Global South and 44 mixed entrant memberships, and 262, 86 and 27 exiter memberships; one AR6 entrant has no listed country. For appointed lead authors, the counts are 69, 49 and 17 entrants and 100, 64 and 15 exiters. Every pair has at least one Global South and one Global North author among both its entrants and its exiters, although the smallest cells hold one or two people. Mixed authors are left out of the main split and added to the Global South group as a robustness check.

Estimator. For geography g, let $E_c^g \subseteq E_c$ and $X_c^g \subseteq X_c$ be the entrants and exiters of pair c classified as g. The own-team gaps $D_c^{5,g}$ and $D_c^{6,g}$ and the two-cycle contrast are computed as in Section S1.10, with E_c^g and X_c^g in place of E_c and X_c. The size benchmark reallocates the labels only among the authors of $E_c^g \cup X_c^g$, keeping $|E_c^g|$ fixed. Instead of simulating it, I compute its expectation exactly: a reference naming m of the $n = |E_c^g \cup X_c^g|$ pooled authors names at least one relabelled entrant with probability $1 - \binom{n-m}{|E_c^g|} / \binom{n}{|E_c^g|}$. This is the limit of the simulated benchmark as $B \to \infty$. Applied to the full rosters, it differs from the simulated benchmark by at most 0.07 percentage points in any chapter. Chapter intervals resample references within chapter and bibliography, and pooled intervals resample whole chapter pairs, as in Section S1.10.

Scale. Global South authors are fewer and are cited far less often in both bibliographies. In the whole team, Global South exiters appear on 1.4% of AR5 references and Global North exiters on 10.5%. A gap in percentage points therefore mixes the size of the shift with the size and visibility of the group. As a scale-free complement, I report the two-cycle fold

$$F^g = \frac{\bar{s}^6(E^g) \,/\, \bar{s}^5(E^g)}{\bar{s}^6(X^g) \,/\, \bar{s}^5(X^g)},$$

the growth from AR5 to AR6 of the entrants' share relative to that of the exiters, where $\bar{s}^k$ pools the 14 pairs with reference weights. A value of one means no relative shift. The fold compares each group with itself, so it does not depend on how often the group is cited overall. Two tests compare the geographies. The first is a pair bootstrap of the Global South minus Global North difference, using the pairs drawn for the two groups' own intervals. The second is a permutation test in which the Global South and Global North labels are shuffled among each pair's entrants and, separately, among its exiters (4,999 draws). This test keeps the group sizes fixed, but its null hypothesis also treats Global South and Global North authors as equally cited.

S2 Journal prestige, secondary references and author footprints

S2.1 Journal prestige and selection intensity

The main-text journal figure colours journals by their 2021 SCImago Journal Rank (SJR). Here I extend the comparison to every journal for which both quantities are available: the 146 journals with an OpenAlex output count for 2005–2021 and a 2021 SJR score. Output was retrieved only for journals with at least ten distinct cited works across the AR5 and AR6 bibliographies (172 journals), and 26 of these have no 2021 SJR score. The 146 journals are a small fraction of the 1,334 journals cited in AR6, but they supply 7,657 of its 10,905 journal-identified references (70.2%). The estimates therefore describe the journals that carry most of the bibliography, not its long tail of rarely cited outlets. Selection intensity is the number of AR6 WGIII references to a journal divided by its output. Output (as in main-text Figure 1B) counts the journal's OpenAlex items excluding errata, book reviews, paratext, conference abstracts, retractions and items typed as other. For *Nature* and *Science*, items without any references are also excluded: their news, comment and correspondence pieces are typed as articles and would otherwise more than double their output. Random samples of the remaining items show such front matter in these two journals only; elsewhere, articles with few or no recorded references are genuine papers, often with incomplete reference lists in OpenAlex. As a further check I use research items only (articles and reviews with at least ten references).

I report two statistics, both giving each journal equal weight (Table S4): the Spearman correlation and the OLS regression of log intensity on log SJR, whose coefficient is the elasticity of selection intensity with respect to SJR. Field fixed effects use the journal's Scimago subject area (economics if any listed area is economics, multidisciplinary if the journal spans three or more areas, otherwise its first listed area; 13 fields). Standard errors are robust to heteroskedasticity.

Table S4: **SJR and AR6 selection intensity across cited journals.** Spearman correlation between selection intensity and SJR 2021 (P value in parentheses), and elasticities of selection intensity with respect to SJR 2021 (robust standard errors in parentheses). OLS: log intensity on log SJR, each journal weighted equally. Field fixed effects (FE) are Scimago subject areas; journals alone in their field are dropped (142 and 48 journals remain). The climate-adjusted row divides by output times the journal's estimated climate share and is subject to the caveats in the text. $^{*}P < 0.05$, $^{**}P < 0.01$.

			OLS elasticity	
Denominator	Journals	Spearman ρ	No FE	Field FE
Publication output	146	0.08 (0.35)	0.12 (0.14)	0.08 (0.14)
Research items	146	0.08 (0.31)	0.08 (0.17)	0.04 (0.18)
Climate-relevant output	50	0.44** (0.002)	0.48** (0.13)	0.51** (0.11)

Output-adjusted intensity. When each journal counts once, selection intensity is unrelated to SJR, whether output is measured as all publications or as research items only, and with or without field fixed effects. The most prestigious journals in the sample are not the most intensively cited: *Nature*, *Science* and the leading general-interest economics journals have SJR scores above 14 but are cited at or near the median rate of 1.3 AR6 references per 100 papers, and *Nature* and *Science* at 0.4–0.5. Restricting the sample to the 145 journals registered as peer-reviewed scientific channels in the Norwegian Register for Scientific Journals (level 1 or 2 in 2021) leaves every estimate essentially unchanged.

Climate-adjusted intensity. Dividing by estimated climate-relevant output (main-text Figure 1C; classification in Section S1.6) yields a positive equal-weight association with SJR among the 50 journals with a climate share (Spearman $\rho = 0.44$). This ratio is the number of AR6

references divided by the journal's estimated climate-relevant output over 2005–2021, a descriptive measure of how much of that output is represented in the AR6 bibliography. I do not read the association as evidence that prestige raises selection, for two reasons.

First, it is largely induced by the denominator. In the same 50 journals, output-adjusted intensity is unrelated to SJR ($\rho = -0.03$), while the climate share falls with SJR ($\rho = -0.49$, $P < 0.001$): the high-SJR journals in this sample are generalist outlets that publish little on climate. A ratio whose numerator, relative to output, is flat in SJR and whose denominator share declines in SJR will tend to rise with SJR. The decomposition is in rank correlations, so it is not an algebraic identity, but it accounts for most of the pattern.

Second, several of the highest ratios rest on small climate shares estimated by keyword classification. *Research Policy* has the highest climate-adjusted intensity (70 AR6 references against an estimated 233 climate-relevant papers, a climate share of 10%), ahead of *Climate Policy* (260 references against 1,171 papers). The *Journal of Economic Perspectives* and the *Quarterly Journal of Economics*, third and fourth, have 13 and 11 references against an estimated 65 and 74 climate-relevant papers, with climate shares below 10%. In such journals, whether a paper's OpenAlex topics mention energy, environment or climate is a noisier guide to its relevance for a mitigation assessment than in specialised journals, and a few references move the ratio substantially.

The association is nonetheless robust to the sensitivity checks. Every journal has at least 50 estimated climate-relevant papers; restricting to the 48 with at least 100 gives a correlation of 0.38 ($P = 0.007$), and excluding the three general-interest economics journals in this sample (*American Economic Review*, *Journal of Political Economy* and *Quarterly Journal of Economics*) gives 0.37 ($P = 0.012$). Climate shares measured on papers published in 2017 or 2024, instead of the 2005–2021 sample, give 0.41 and 0.38.

What a proper test would require. Whether a climate-relevant paper is more likely to be cited because it appears in a high-SJR journal is a paper-level question. It requires comparing papers on the same topic published in journals of different standing, including journals that AR6 does not cite. The paper-level selection models do not answer it: every choice set is drawn from a single journal and year, so journal standing is absorbed by the choice-set fixed effects. At the journal level, the evidence shows only that journal standing does not consistently predict AR6 citation intensity, and that the association depends on how the opportunity to be cited is measured. The sample contains only journals cited at least once in AR6 WGIII, so these estimates describe variation among cited journals, not the probability that a journal is cited at all.

S2.2 Author publication footprints and geography

Stratifying the cited papers by author-team geography shows where papers from each group appear (Figure S2). Global South-only papers are relatively frequent in *Renewable and Sustainable Energy Reviews* and the *Journal of Cleaner Production*. These counts describe where selected papers appear. The paper-level models ask the different question of whether a Global South-only paper is more or less likely to be selected than available papers from the same journal and year (main-text Table 2).

S2.3 Journal communities across chapters

AR6 WGIII chapters do not draw on a common literature in equal proportions (Figure S3). Journals are grouped into eight descriptive clusters (Section S1.5), and the figure shows the most-cited journals in each. The framing chapters lean on global-change and environmental-science outlets: *Nature Climate Change* and *Environmental Research Letters* each supply 15% of the clustered references in Chapter 3 on mitigation pathways. Sectoral chapters draw on

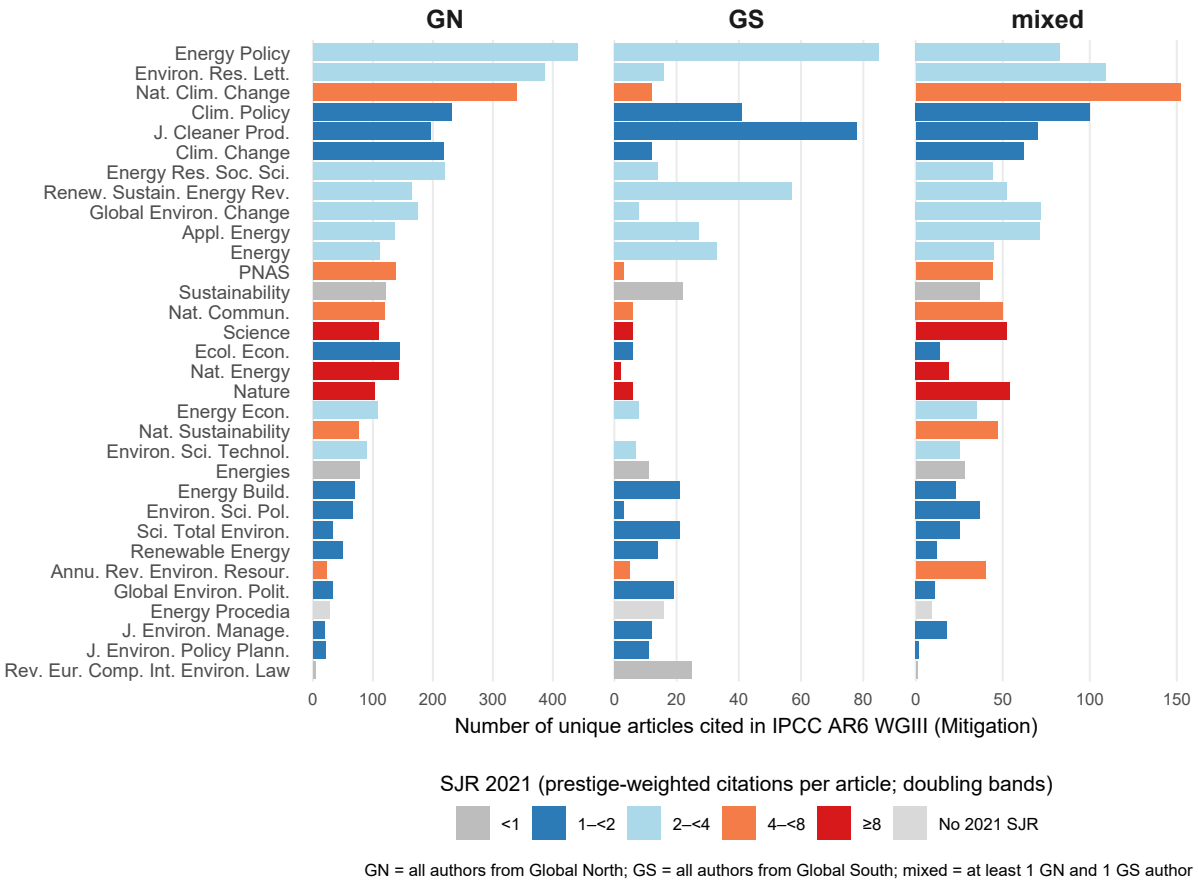


Figure S2: **Journal citation counts by author geography.** The journal list is the union of the 20 most-cited journals in each of the three groups, which gives 32 journals. Papers are classified as Global North-only, Global South-only or mixed (at least one Global North and one Global South author) from publication-time affiliations. Colour denotes the journal's 2021 SCImago Journal Rank in fixed doubling bands, as in main-text Figure 1 (Section S1.4); *Energy Procedia*, discontinued in 2019, has no 2021 score.

technically specialised journals, such as *Energy and Buildings* (15%) in Chapter 9 on buildings and the *Journal of Cleaner Production* (20%) in Chapter 11 on industry. Policy and governance outlets are most prominent in the cross-cutting chapters, with *Climate Policy* supplying 22% in Chapter 14 on international cooperation and 14% in Chapter 13 on national policies. The multidisciplinary journals are most prominent in Chapter 7 on agriculture, forestry and land use. *Energy Policy* is cited in every chapter and supplies 10% or more of the clustered references in eight of them, across both sectoral and governance chapters.

This division of labour is consistent with the main-text finding that bibliographic alignment with the writing team is strongest in the authors' own chapters: each chapter assembles a different combination of research communities, so the expertise of its authors bears most directly on its own literature. The clusters are descriptive and the figure covers only the displayed journals.

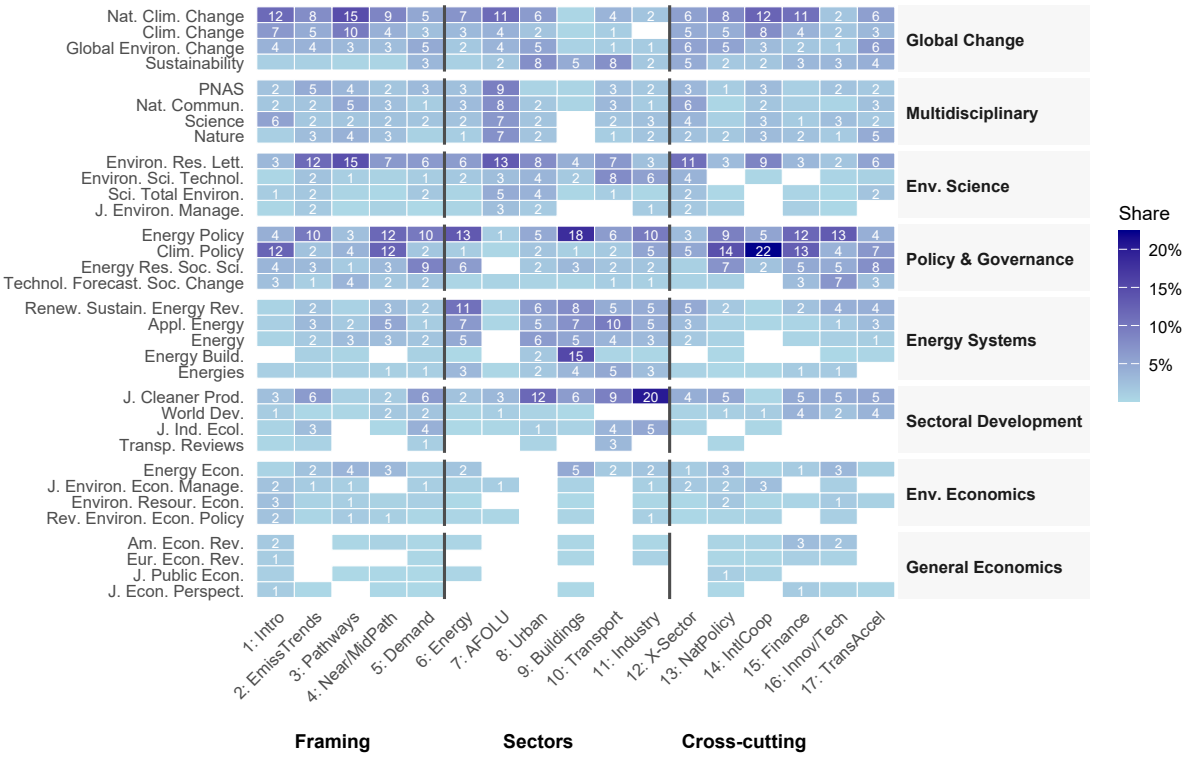


Figure S3: **Journal communities across AR6 WGIII chapters.** Each cell is the share of a chapter's references to the 90 clustered journals that come from the journal shown, in percent; values below 1% are not labelled. Only the most-cited journals of each descriptive cluster are displayed, so shares do not sum to 100% within a chapter. Chapters are grouped into framing (Chapters 1–5), sectoral (6–11) and cross-cutting (12–17) chapters.

S3 Reference persistence, turnover estimator and chapter-level results

S3.1 Persistence of references between assessment cycles

Figure S4 breaks down by journal the reuse of AR5 references reported in the main text. Reuse is highest, at around 30%, in a few smaller outlets such as *Nature Climate Change*, *PNAS* and *Technological Forecasting and Social Change*. It is lowest in the journals that supplied most of AR5's literature: 8.2% of *Energy Policy*'s AR5 works reappear in AR6, and 6.2% of those from *Renewable and Sustainable Energy Reviews*. Newer interdisciplinary journals expanded most between the two reports, while *Energy Policy* remained the largest source in both.

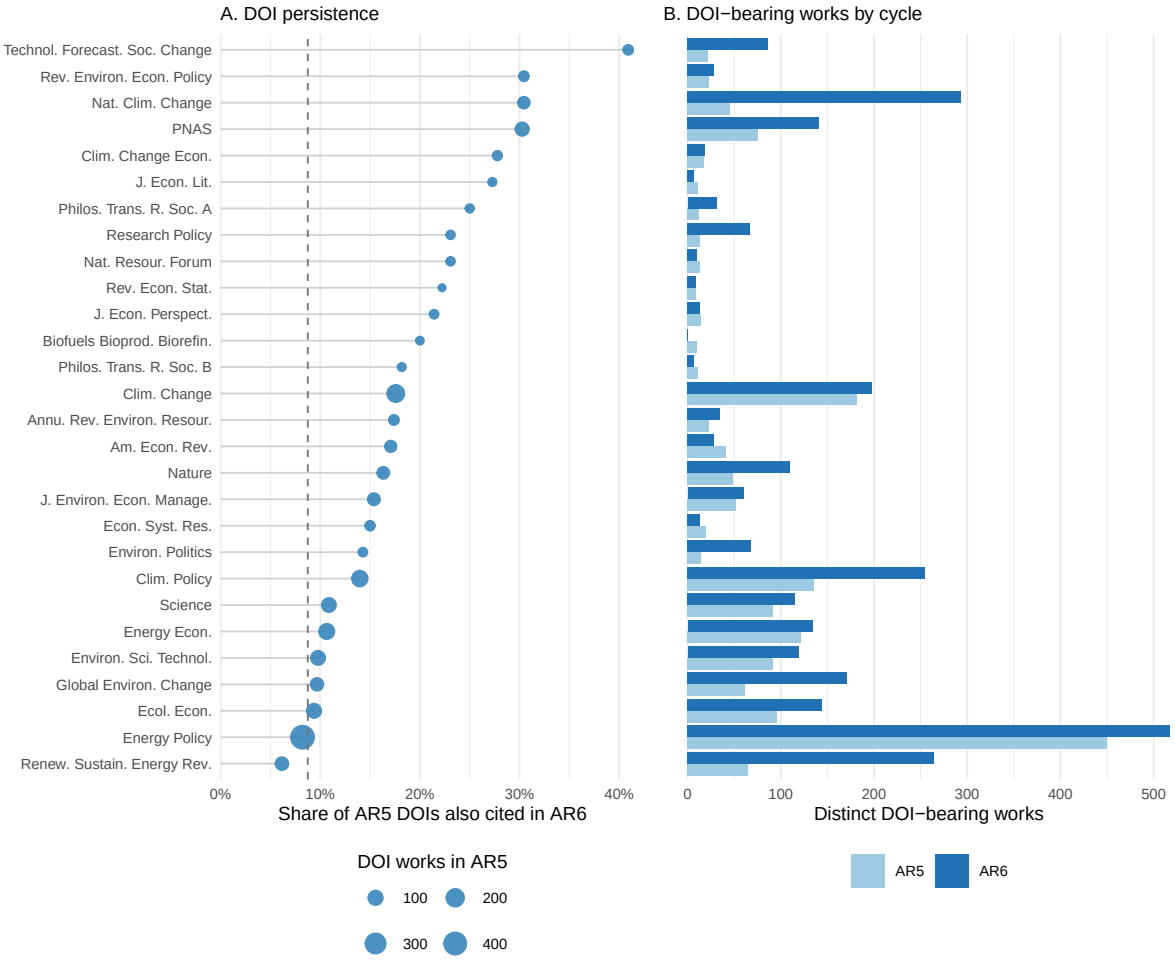


Figure S4: **Reference persistence and volume across AR5 and AR6.** (A) Share of each journal's AR5 DOI works that are also cited in AR6, for the 20 journals with the highest persistence among those with at least eight AR5 works and the 10 journals with most AR5 works. Point size gives the number of AR5 works; the dashed line marks the overall rate of 8.8%. (B) Distinct DOI works from the same journals in AR5 and AR6, in the same order.

S3.2 Chapter-level estimates and sensitivity

The chapter crosswalk (Table S2) matches AR5 and AR6 chapters, but some matches are closer than others. Table S5 therefore repeats the comparison on three subsets. The first excludes the three loosest matches (marked †): AR6 Chapters 1 (*Introduction and framing*), 4 (*Mitigation and development pathways in the near- to mid-term*) and 5 (*Demand, services and social aspects*

of mitigation), whose broad scope is the most likely to have shifted between reports. The second keeps only the six sectoral pairs, whose scope is most stable. The third computes shares only over references with a usable author key, which is missing more often in AR5. None of these restrictions changes the results materially.

Table S5: **Sensitivity to the chapter crosswalk and to author-key coverage.** Percentage points; each included chapter pair has equal weight. Brackets give 95% percentile intervals from resampling chapter pairs.

	Entrants' share (change)	Exiters' share (change)	Adjusted two-cycle contrast
A. Whole writing team (CLA + LA + CA)			
All 14 pairs (main)	7.9 [6.1, 9.8]	−7.5 [−8.6, −6.5]	15.2 [13.1, 17.4]
11 same-subject pairs	7.7 [5.4, 10.0]	−7.7 [−8.9, −6.4]	15.1 [12.6, 17.7]
6 sectoral pairs	7.0 [4.4, 9.5]	−7.1 [−8.9, −5.4]	13.7 [10.7, 16.7]
Keyed references only	7.6 [5.8, 9.5]	−8.8 [−10.1, −7.6]	16.4 [14.4, 18.4]
B. Appointed lead authors (CLA + LA)			
All 14 pairs (main)	3.6 [2.4, 5.0]	−4.6 [−5.8, −3.4]	8.0 [6.5, 9.7]
11 same-subject pairs	3.2 [1.9, 4.9]	−4.6 [−6.0, −3.2]	7.5 [5.8, 9.7]
6 sectoral pairs	3.2 [2.0, 4.3]	−3.7 [−5.7, −1.9]	6.7 [5.2, 8.4]
Keyed references only	3.5 [2.3, 4.8]	−5.5 [−7.0, −4.1]	8.6 [7.0, 10.4]

Notes: The 11 pairs with the same named subject leave out AR6 Chapters 1, 4 and 5, whose AR5 counterparts differ in scope (an introductory chapter; sustainable development and equity; social, economic and ethical concepts and methods; Table S2). The sectoral pairs are AR6 Chapters 6–11: energy, AFOLU, urban systems, buildings, transport and industry. Keyed references only: shares divide by the references with at least one usable author key (91.2% of AR5 and 99.2% of AR6 reference–chapter pairs) instead of all references; a reference without a key cannot match either group, so this rescales each bibliography's shares, gaps and size benchmarks. In every variant, the entrants' share rises and the exiters' share falls in every included pair. With six pairs, the sectoral intervals are particularly rough.

S3.3 Continuing authors and appointment roles

Figure S5 adds the continuing authors, 52 chapter memberships in 11 of the 14 pairs, to the bars of main-text Figure 5, and splits each bar by appointment role. The continuing authors' share barely moves between the two bibliographies (0.6 points on average; interval −0.2 to 1.7). Their retention is itself selected, so they are not a control group. Because continuing authors are few, the incoming and outgoing authors make up almost nine in ten members of each matched team (460 of the 512 AR6 and 375 of the 427 AR5 chapter memberships), so the turnover comparison covers nearly the whole writing team.

S3.4 Own chapter and other matched chapters

Table S6 follows the same entrants and exiters into the bibliographies of the other matched chapters, which they did not write. Under both roster definitions and in both cycles, the adjusted gap is larger in the authors' own chapter in all 14 pairs.

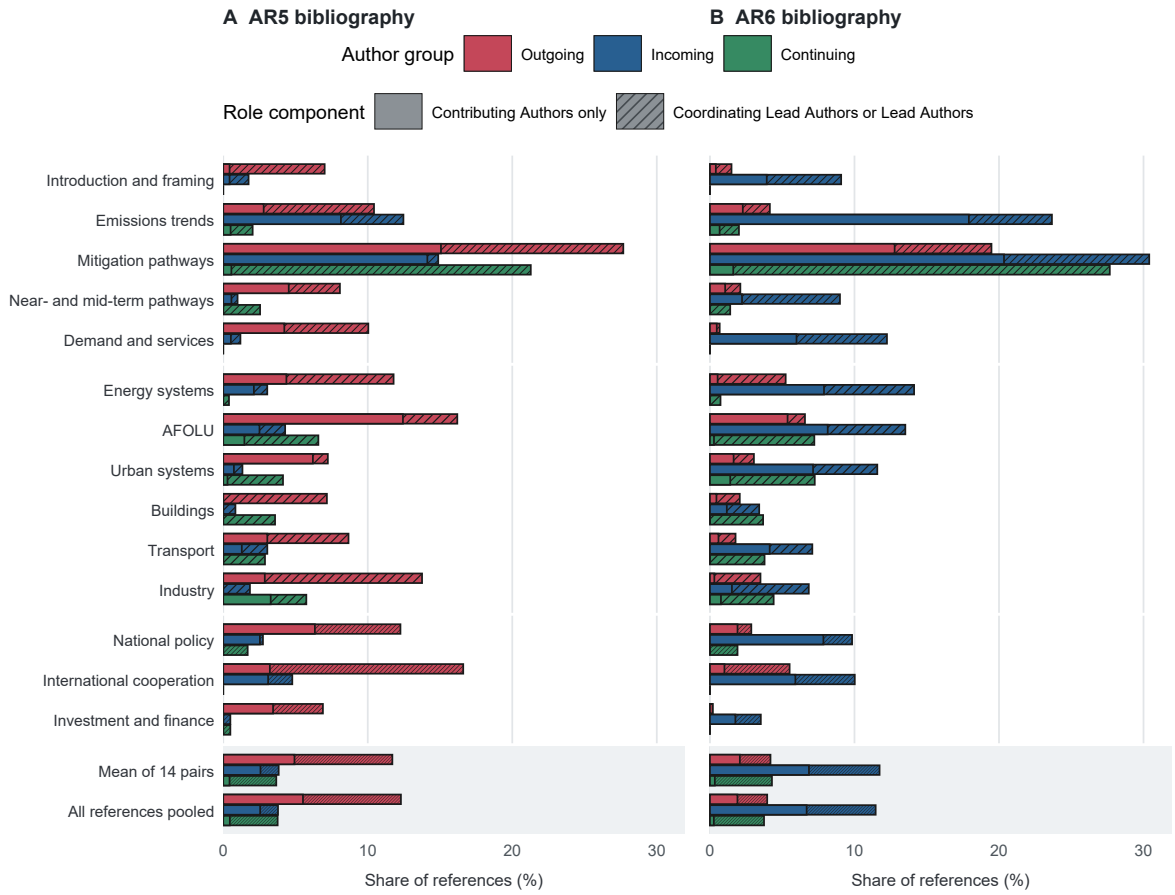


Figure S5: **Citation shares by turnover group and appointment role.** As main-text Figure 5, with continuing authors, who served on both matched rosters, added in green. The striped portion of each bar names at least one Coordinating Lead Author or Lead Author of that group; the unpatterned portion names only its Contributing Authors. The two portions are mutually exclusive, so bar totals reproduce main-text Figure 5. An author who was a Coordinating Lead Author or Lead Author in either assessment counts as lead-linked in both bibliographies. The shaded rows average the 14 pairs with equal weights or pool all references.

Table S6: Specificity of the entrant–exiter citation gap in the AR6 bibliography: each chapter's own bibliography against the other matched chapters

	Whole team (CLA + LA + CA)		Lead authors (CLA + LA)	
	Own chapter	Other chapters	Own chapter	Other chapters
References linked to entering authors (%)	11.5	3.0	5.6	0.9
References linked to exiting authors (%)	4.0	1.7	2.8	0.9
Size-adjusted gap (percentage points)	6.3	0.9	3.8	0.2

Notes: The primary roster is the whole credited writing team (Coordinating Lead Authors, Lead Authors, and Contributing Authors); the last two columns restrict it to appointed lead authors. Shares are pooled across 14 hand-matched AR5–AR6 chapter pairs using own-chapter reference counts as weights. AR6 Chapter 3 is matched to AR5 Chapter 6; AR6 Chapters 12, 16, and 17 are excluded. The size-adjusted gap subtracts the mean gap under 9,999 size-preserving reallocations of authors within each pair.

S3.5 References close to the chapter outline

Each cited paper is scored against the 17 chapters of the WGIII outline adopted in September 2017, before author selection (Section S1). A score requires a DOI and usable text (abstract or OpenAlex concepts), available for 72% of reference–chapter pairs. Each restricted sample is therefore compared with this text-available set rather than with the full sample (Table S7). The gap remains positive and of similar size when the citing chapter must be among the paper's best-matching chapters, and it rises among references most similar to the outline. These are descriptive checks: the classifier ranks the actual citing chapter first for 29.3% of cited papers and among the top three for 52.5%, so the restricted samples are noisy, and topical relevance cannot separate recruitment for a chapter's remit from attention to the authors' own work.

Table S7: **AR6 entrant–exiter gap among references close to the chapter outline.** Size-adjusted gap in percentage points, pooled over the 14 matched chapters with reference weights; 95% chapter-pair intervals in brackets.

Reference–chapter pairs	N	Whole team	Lead authors
All	14,138	6.3 [4.7, 7.8]	3.8 [2.7, 4.9]
With paper text (baseline)	10,165	7.4 [5.5, 9.1]	4.4 [2.9, 5.8]
Restrictions of the baseline			
Citing chapter among the paper's top three	4,701	7.9 [6.1, 9.2]	4.0 [2.9, 5.6]
Citing chapter ranked first	2,449	7.7 [6.2, 9.1]	3.3 [2.4, 4.5]
Upper half of similarity within chapter	5,085	8.5 [6.3, 10.5]	4.8 [2.8, 7.0]
Upper quartile of similarity within chapter	2,545	10.6 [7.6, 13.0]	6.3 [3.7, 9.2]

S3.6 Global North and Global South authors

The own-chapter citation pattern holds in both the Global North and Global South. For the whole writing team, the adjusted two-cycle contrast is 12.5 percentage points for Global North authors [10.5, 14.5] and 1.8 for Global South authors [1.3, 2.4], and it is positive in all 14 pairs for both. The Global North gap is positive in every pair in both bibliographies. The Global South gap is positive in 12 of 14 pairs in each bibliography, but its chapter estimates are small and their intervals exclude zero in only seven pairs. In percentage points, the difference between the geographies is large (-10.6 [-12.5, -8.8]). It is also larger than the label permutation predicts from group size alone (-6.9 [-8.5, -5.2]; $p = 0.0002$). Because that permutation also assumes equal citation levels, this comparison cannot distinguish a weaker shift from lower visibility. Relative to its own share, the entrants' share grew 9.3-fold against the exiters' for Global North authors [5.3, 20.3] and 6.9-fold for Global South authors [4.0, 18.3]. The ratio of the two folds is 0.74 [0.29, 2.24], so neither geography shows a detectably stronger proportional shift.

The same holds for appointed lead authors: a two-cycle contrast of 5.7 [4.4, 7.0] for Global North authors against 1.4 [0.8, 2.1] for Global South authors, with folds of 6.5 and 7.1 (ratio 1.10 [0.27, 4.30]). On references published by 2013, the Global South contrast stays positive (1.3 [0.8, 1.9] for the whole team; 1.2 [0.7, 1.8] for lead authors). As for the full rosters (Section S3.7), the AR6 gap shrinks on this older literature, to 0.3 [0.0, 0.7] for Global South authors of the whole team, against 2.2 [0.3, 4.1] for Global North authors. Counting mixed authors as Global South raises the Global South contrast to 3.0 [2.4, 3.9] for the whole team and 2.3 [1.7, 3.0] for lead authors. Alignment with the writing team is therefore found in both geographies. Global North authors carry most of its weight in the bibliographies, because they make up most of the teams and their work is cited most often. Relative to each group's own citation level, the data cannot tell which geography shifted more.

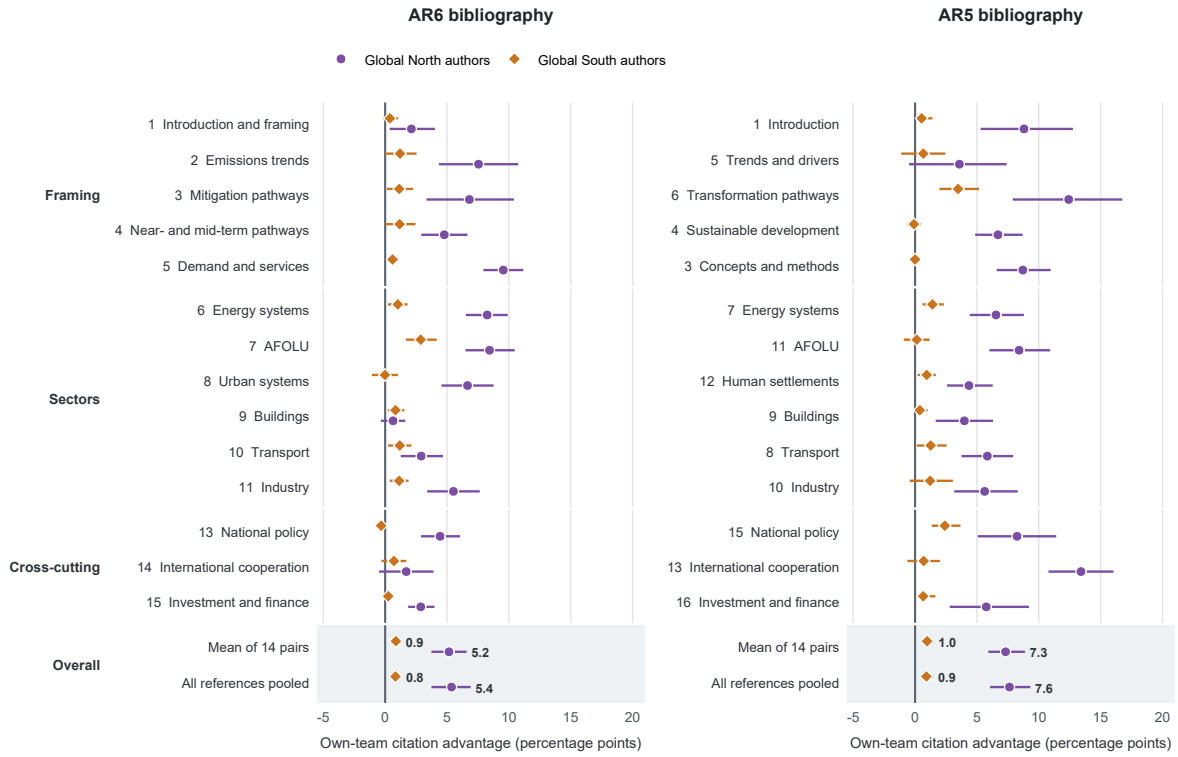


Figure S6: **Own-team citation advantage of Global North and Global South authors.** Whole credited writing team (CLA + LA + CA). For each bibliography, the share of references naming the geography's own-team authors minus the share naming its other-team authors (AR6: entrants minus exiters; AR5: exiters minus entrants), computed separately for Global North (circles) and Global South (diamonds) authors, after subtracting the expected gap under size-preserving reallocations within that geography. Authors listing countries in both groups are left out. Chapter whiskers are 95% percentile intervals from resampling references within each chapter and bibliography. In the shaded rows, the 14 pairs are averaged with equal weights or all references are pooled, and their whiskers resample whole chapter pairs.

S3.7 Literature of the same age

AR6 could cite work published after AR5, and active AR6 authors may have produced more of it. I therefore restrict both bibliographies to references published by 2013, which leaves 8,043 AR5 and 2,045 AR6 references (open points in Figure S7). The pattern keeps its direction but weakens. Averaged over pairs, the exiters' share falls by 6.3 points (−7.9 to −4.8; all 14 pairs) and the entrants' share rises by 5.7 points (3.5 to 8.2; 12 pairs). The adjusted AR6 entrant–exiter gap falls from 6.1 to 3.0 points (1.0 to 4.9; positive in 10 pairs), and the two-cycle contrast from 15.2

to 11.9 points (9.4 to 14.4), mostly because the restriction barely affects the AR5 bibliography. For appointed lead authors, the restricted AR6 gap is 1.6 points (−0.3 to 3.8).

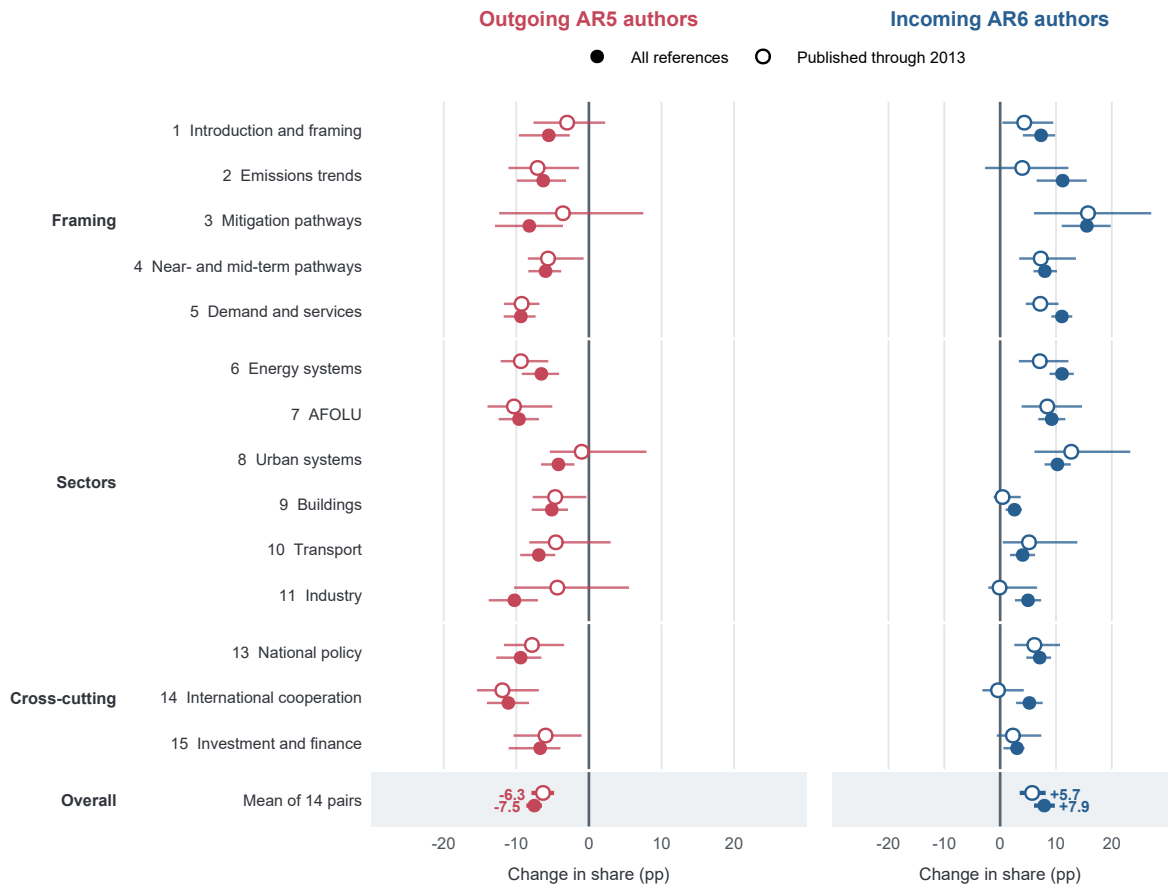


Figure S7: **Changes in citation shares for the outgoing AR5 and incoming AR6 authors.** Each point is the change in a group's share of a chapter's references between the matched AR5 and AR6 bibliographies; positive values mean a larger share in AR6. Both groups are whole credited writing teams. Filled points use all references; open points retain only references published by 2013. Thin whiskers are 95% Newcombe score intervals for the difference between the two reference shares within a chapter. The shaded row averages the 14 matched pairs with equal weights; its heavier whiskers resample whole chapter pairs.

Publication bands. A single cut-off cannot separate work the AR6 authors published while serving from recent work they had published before their appointment. Table S8 therefore splits each bibliography by the publication year of the cited work. Alignment concentrated in work from 2018 onwards would point to the authors' own output while serving; in 2014–2017, to the recruitment of people with recent relevant work; in work up to 2009, to the reselection of older literature. The size benchmark is computed exactly within each band (on the full bibliographies it matches the permutation means to within 0.3 points).

For the whole writing team, the AR6 gap is 7.9 points for work published from 2018 (positive in all 14 pairs), 4.6 for 2014–2017 (13 pairs), 4.2 for work up to 2009 (0.4 to 8.0; 9 pairs), and 2.0 for 2010–2013, with an interval that includes zero. All three channels contribute, but recent work carries most of the alignment. The AR5 bibliography shows the same gradient: 10.8 points for work published in 2010–2014 against 7.0 for earlier work. For lead authors, the AR6 gap is 4.5 points from 2018 and 3.5 for 2014–2017, and cannot be distinguished from zero before 2014.

Publication supply. Before 2014, outgoing authors published more than incoming ones: 3.7 against 2.3 works per author-year in 2000–2009, and 6.4 against 5.4 in 2010–2013 (Figure S8). Yet on this literature the AR6 bibliography names incoming authors more often, with an adjusted gap of 3.0 points. From 2016 the supply difference reverses, so for recent work supply and alignment cannot be separated.

Table S8: **Own-team gaps by publication year of the cited work.** Size-adjusted own-team gap in percentage points; each chapter pair has equal weight. Brackets give 95% percentile intervals from resampling chapter pairs; parentheses give the number of pairs with a positive gap.

Published	References	Whole writing team (CLA + LA + CA)	Lead authors (CLA + LA)	Works per author-year incoming vs outgoing
AR6 bibliography (incoming minus outgoing authors)				
Up to 2009	793	4.2 [0.4, 8.0] (9/14)	1.8 [−0.1, 4.0] (7/14)	2.3 vs 3.7
2010–2013	1,252	2.0 [−0.7, 4.7] (8/14)	1.6 [−1.0, 4.4] (9/14)	5.4 vs 6.4
2014–2017	4,453	4.6 [3.1, 6.2] (13/14)	3.5 [2.2, 4.9] (12/14)	6.9 vs 6.7
2018 and later	7,640	7.9 [6.3, 9.4] (14/14)	4.5 [3.1, 6.0] (13/14)	8.2 vs 6.1
AR5 bibliography (outgoing minus incoming authors)				
Up to 2009	3,761	7.0 [4.9, 9.2] (13/14)	3.9 [2.4, 5.5] (13/14)	2.3 vs 3.7
2010–2014	4,340	10.8 [8.6, 13.1] (14/14)	4.2 [2.9, 5.5] (13/14)	5.6 vs 6.6

Notes: The adjusted gap subtracts the expected gap when the pooled incoming and outgoing authors of a pair are reallocated at random to groups of the observed sizes, computed exactly within each band. Works per author-year are mean OpenAlex works per author in the band's publication years for the whole writing teams (352 incoming and 306 outgoing authors; years 2000–2009 for the first band, 2018–2020 for the last). The AR5 bibliography's second band includes 58 references from 2014. Bands with few references per chapter (as few as 10 in AR6 up to 2009) give imprecise chapter values.

S3.8 Concentration in the matched chapter

Absolute citation shares are hard to compare between groups cited at very different rates, such as authors and Review Editors. A measure that does not depend on how often a group is cited is the concentration of its citations in the chapter it is matched to: the share of that chapter's AR6 references naming a member, divided by the share of the other matched chapters' references naming one. Researchers working on a chapter's subject are likely to be cited more in that chapter whether or not they write it, so the ratio exceeds one for any group matched to the chapter by subject. The comparison asks whether the experts who wrote the chapter are more concentrated in it than experts appointed for the same subject who did not.

Table S9 reports the ratio for three groups of appointed experts in three reports. For each AR6 chapter, the groups are its Coordinating Lead Authors and Lead Authors together, its Coordinating Lead Authors alone, and its Review Editors, and the same three groups for its AR5 predecessor and for the AR7 chapter or chapters mapped to it through the crosswalk. Only the AR6 Coordinating Lead Authors and Lead Authors wrote the chapter. Review Editors are appointed through the same process as the authors and, like Coordinating Lead Authors, number two or three per chapter and hold a senior role (IPCC Working Group III, 2018), but they oversee the handling of review comments and do not draft the text. To keep the comparison groups non-writing, I drop AR5 and AR7 members who held any role in the matched AR6 chapter (for the lead-author teams, 42 of 207 AR5 and 33 of 179 AR7 chapter memberships) and Review Editors who also wrote the chapter they reviewed. A member is also not counted in another AR6 chapter in which they held a role. All groups include experts at every career stage, whether or not they served in earlier reports.

Every non-writing group is concentrated in its matched chapter, to a similar degree. Over all publication years, the AR5 and AR7 lead-author teams are cited 3.5 and 3.4 times as often in the matched chapter as in the other matched chapters (95% intervals from resampling matched chapters, 2.4 to 4.7 and 2.3 to 5.0), the AR5 and AR7 Coordinating Lead Authors 2.6 and 4.7

times, and the Review Editors of the AR5, AR6 and AR7 chapters 2.6, 2.9 and 2.0 times. The groups that wrote the chapter are much more concentrated: the AR6 lead-author team is cited 8.0 times as often in it as elsewhere (6.4 to 10.3), and its Coordinating Lead Authors 9.0 times (6.4 to 13.7). Because the ratio compares each group against itself, these comparisons do not depend on how often a group is cited, which differs widely: the AR6 Review Editors appear on 0.07% of the other matched chapters' references, against 0.26% for the AR6 Coordinating Lead Authors. For the lead-author teams, the difference holds in every publication period: the AR6 ratio ranges from 7.1 to 9.2 for work published from 2014, against 3.0 to 3.8 for the AR5 and AR7 teams, and reaches 15.7 for work published by 2013, against 4.5 and 3.5. Groups of two or three members per chapter appear on few references in any one period, so their estimates by period are imprecise.

The non-writing groups are matched to the chapter in different ways (the AR5 groups to its direct predecessor, the AR7 groups through a crosswalk, the AR6 Review Editors to the chapter itself), at different times and in different roles, yet their ratios are similar, at 2.0 to 4.7. Being appointed for a chapter's subject without writing it thus goes with a concentration of about three, and the experts who wrote the chapter are cited there two to three times as intensively. The AR6 Review Editors were appointed to the same chapters at the same time as the authors, so their comparison holds the scope fixed, and they are no more concentrated than the experts appointed for the AR5 and AR7 chapters. Taking the non-writing groups' work to be as relevant to the chapter as the writers', the writers' excess concentration is the effect of writing it: had their work been concentrated like that of their counterparts, they would appear on about 3% of the chapter's references instead of 7.3%, so more than half of their presence comes from writing the chapter.

The same comparison within the AR5 bibliography gives 11.8 for the AR5 Coordinating Lead Authors, who wrote the chapters (8.6 to 15.5), and 6.1 for the AR5 Review Editors (2.3 to 13.8). The Review Editors' ratio rests largely on a single Review Editor, who appears on 25 of the 61 references naming a Review Editor in the chapter they oversaw.

S3.9 Publication records of incomers and exiters

Entrants might also differ from exiters in ways that would raise their citation share whoever wrote the chapter. To check, I compare the two groups' publication records before AR6 began. in the main estimates, this comparison uses the whole writing rosters, including Contributing Authors, linked to OpenAlex: 352 incomers and 306 exiters, excluding dataset records.

Publication output. Incomers were not more prolific than the authors they replaced (Fig. S8). Before AR5 appeared, exiters published more each year. Over 2000–2016 they averaged 4.91 works per year against 3.81 for incomers (difference −1.10; 95% CI −2.07 to −0.14). The two series converge in 2014–2015, before the AR6 authors were selected in January 2018. Incomers therefore had less work available for citation than exiters. On its own, this would lower their share of citations.

Restricting OpenAlex records to articles and reviews weakens this difference but does not reverse it. Over 2000–2016, incomers averaged 2.55 articles or reviews per author-year and exiters averaged 2.93, a difference of −0.38 (author-clustered 95% CI −1.00 to 0.30). Thus the stronger claim that exiters published significantly more depends partly on counting a broader set of scholarly works, but the relevant diagnostic conclusion does not: incomers did not have more article and review output available for citation.

Research profiles. Chapter by chapter, the broad research areas of the AR6 team resemble those of the AR5 team it replaced (Figs. S9 and S10). I describe each team by the average share of its members' 2000–2016 works in each OpenAlex subfield or topic, giving every author equal

Table S9: **Concentration of citations in the matched chapter for experts appointed in AR5, AR6 and AR7, by role and publication year of the cited work.** (A) Share of the matched AR6 chapter's references naming a group member. (B) Share of the other matched AR6 chapters' references naming a group member. (C) Ratio of A to B.

Published	Up to 2013	2014–2017	2018–2020	2021 and later	All years
(A) Matched chapter (% of references)					
AR5 CLAs and LAs	2.15	2.27	1.73	2.40	2.02
AR5 CLAs	0.44	0.28	0.29	0.41	0.32
AR5 Review Editors	0.29	0.09	0.06	0.00	0.10
AR6 CLAs and LAs (writing)	6.26	7.19	6.73	13.04	7.33
AR6 CLAs (writing)	1.52	2.85	1.76	5.23	2.36
AR6 Review Editors	0.20	0.20	0.22	0.17	0.21
AR7 CLAs and LAs	0.49	1.24	1.62	3.43	1.49
AR7 CLAs	0.16	0.12	0.22	0.63	0.21
AR7 Review Editors	0.15	0.04	0.08	0.26	0.09
(B) Other matched chapters (% of references)					
AR5 CLAs and LAs	0.48	0.66	0.51	0.77	0.58
AR5 CLAs	0.12	0.12	0.11	0.22	0.12
AR5 Review Editors	0.06	0.03	0.04	0.01	0.04
AR6 CLAs and LAs (writing)	0.40	0.98	0.95	1.41	0.92
AR6 CLAs (writing)	0.07	0.31	0.24	0.50	0.26
AR6 Review Editors	0.03	0.07	0.08	0.06	0.07
AR7 CLAs and LAs	0.14	0.42	0.47	0.90	0.44
AR7 CLAs	0.02	0.04	0.04	0.12	0.05
AR7 Review Editors	0.02	0.04	0.06	0.07	0.05
(C) Ratio, matched to other chapters					
AR5 CLAs and LAs	4.5 [2.4, 8.3]	3.4 [2.2, 4.4]	3.4 [2.3, 4.6]	3.1 [1.5, 5.3]	3.5 [2.4, 4.7]
AR5 CLAs	3.6 [0.7, 8.7]	2.4 [1.0, 4.1]	2.6 [0.8, 4.9]	1.9 [0.6, 3.3]	2.6 [1.2, 4.1]
AR5 Review Editors	5.2 [1.3, 17.7]	2.7 [0.0, 7.2]	1.4 [0.0, 5.1]	0.0 [0.0, 0.0]	2.6 [0.7, 6.4]
AR6 CLAs and LAs (writing)	15.7 [10.0, 25.4]	7.3 [6.0, 9.6]	7.1 [5.4, 9.6]	9.2 [6.7, 12.7]	8.0 [6.4, 10.3]
AR6 CLAs (writing)	21.2 [11.0, 93.9]	9.1 [7.0, 13.0]	7.2 [4.4, 12.9]	10.4 [7.1, 17.0]	9.0 [6.4, 13.7]
AR6 Review Editors	5.8 [0.0, 24.0]	2.8 [1.0, 10.9]	2.6 [1.2, 5.6]	2.9 [0.0, 13.8]	2.9 [1.3, 6.6]
AR7 CLAs and LAs	3.5 [1.2, 8.2]	3.0 [1.9, 4.3]	3.4 [2.3, 5.3]	3.8 [2.4, 6.3]	3.4 [2.3, 5.0]
AR7 CLAs	6.5 [0.0, 16.5]	3.5 [0.0, 9.9]	4.8 [1.2, 15.4]	5.2 [1.3, 13.1]	4.7 [1.2, 12.9]
AR7 Review Editors	7.8 [0.0, 30.2]	1.1 [0.0, 5.7]	1.4 [0.6, 6.0]	3.9 [0.0, 6.5]	2.0 [1.2, 6.3]

Notes: AR6 bibliography of the 14 matched chapters. Each group consists of the Coordinating Lead Authors (CLAs), Lead Authors (LAs) or Review Editors of the AR6 chapter, of its AR5 predecessor, or of the AR7 chapter(s) mapped to it through the crosswalk in Table S2. Only the AR6 CLAs and LAs wrote the chapter. AR5 and AR7 members with any role in the AR6 chapter are excluded, as are Review Editors who also wrote the chapter they reviewed. Other chapters are counted as reference–chapter pairs, and a member is not counted in a chapter to which the same group also assigns them or in which they held any AR6 role. Brackets give 95% percentile intervals from resampling matched chapters. Shares are not adjusted for group size, which cancels in the ratio. Groups of two or three members per chapter (CLAs, Review Editors) appear on few references in any one period, so their intervals by period are wide.

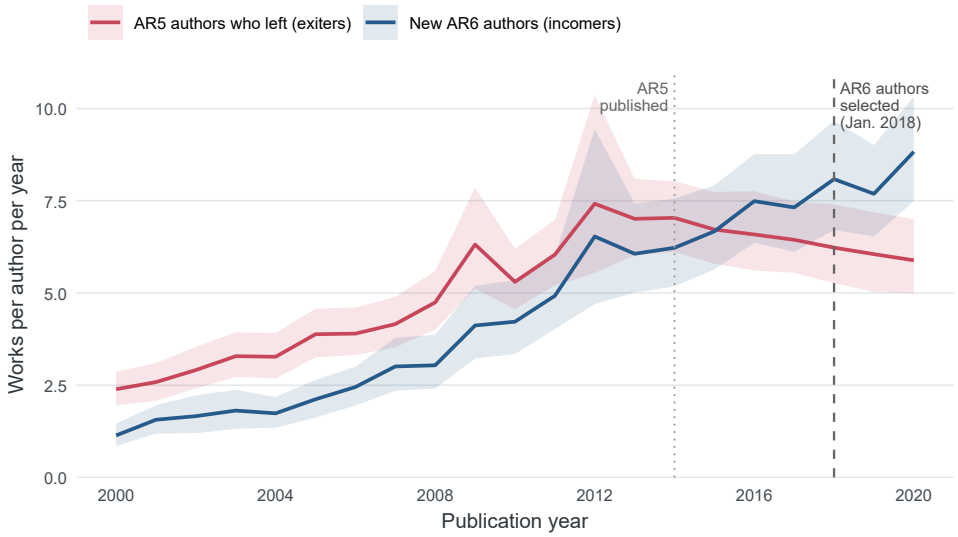


Figure S8: **Annual publication output of AR5 exiters and AR6 incomers.** Works per author per year in OpenAlex, 2000–2020, for the whole writing rosters (352 incomers and 306 exiters linked to OpenAlex; dataset records excluded). Bands are 95% confidence intervals. The dotted line marks the publication of AR5 (2014); the dashed line marks the selection of the AR6 author team by the Working Group III Bureau (January 2018).

weight, and compare the AR5 and AR6 profiles of each matched chapter. In each chapter, the dominant research areas lie close to the diagonal, where both teams have the same shares.

To summarise each chapter, I use the Jensen–Shannon similarity. It equals 1 for identical profiles and 0 for profiles that share no research area. Across the 14 matched chapters, the median similarity is 0.83 for subfields (range 0.71–0.91) and 0.58 for the finer topics (0.46–0.75). As a benchmark, an AR5 team compared with the AR6 team of a *different* chapter scores a median of 0.70 for subfields and 0.45 for topics. In 9 of 14 chapters for subfields, and 10 of 14 for topics, the AR6 team is closer to its own predecessor than to any other chapter's AR5 team. The exceptions are broad framing and policy chapters (1, 4, 5, 14, and 15). Their AR6 teams are slightly closer to the economics-heavy AR5 teams of the national-policy or pathway chapters, which draw on overlapping literatures.

Comparing only exiters and incomers, and so leaving out continuing authors, gives medians of 0.76 for subfields and 0.46 for topics. These values are lower partly because smaller groups produce sparser and noisier profiles, so they need their own benchmark. The exiters of one chapter compared with the incomers of a different chapter score a median of 0.64 for subfields and 0.37 for topics. The incomers of a chapter are more similar to its own exiters than to the median other chapter's exiters in 13 of 14 chapters for subfields and in all 14 for topics, but their own chapter's exiters are the most similar group in only six. Pooled across all chapters, the field-level profiles of incomers and exiters are almost identical (similarity 0.975 over 2000–2016). These checks concern observable research output only. Similar broad profiles do not show that individual papers were equally relevant to the questions AR6 addressed, and they cannot rule out differences that publication records do not capture.

The profile comparison is also stable when the underlying OpenAlex records are restricted to articles and reviews. For the full chapter teams, median same-chapter similarity changes from 0.83 to 0.81 for subfields and from 0.58 to 0.56 for topics; the corresponding different-chapter benchmarks remain 0.70 and 0.45. Comparing only exiters with incomers gives medians of 0.74 for subfields and 0.43 for topics, against 0.76 and 0.46 with all non-dataset works. These remain above the article-and-review different-chapter benchmarks of 0.63 and 0.36. The substantive conclusion therefore does not depend on including books, chapters, reports, preprints, or other

OpenAlex work types.

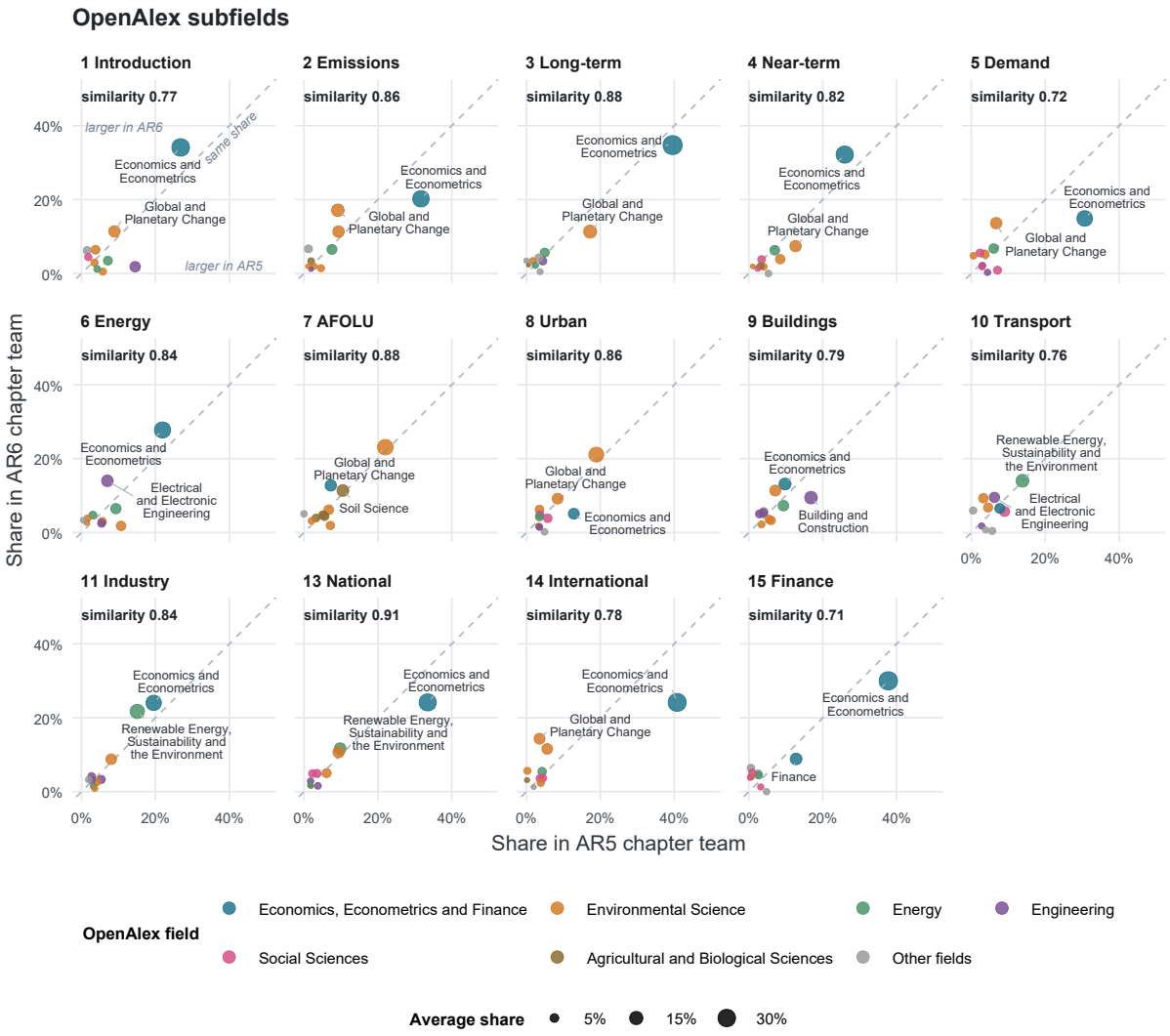


Figure S9: **Research profiles of the AR5 and AR6 chapter teams, OpenAlex subfields.** Each panel is one matched chapter. Each point is an OpenAlex subfield; its position gives the average share of the team members' 2000–2016 works in that subfield, in the AR5 team (horizontal axis) and the AR6 team (vertical axis), with every author weighted equally. Points on the dashed diagonal have the same share in both teams. Point size is the average of the two shares, and colour gives the OpenAlex field. The label reports the Jensen–Shannon similarity of the two profiles.

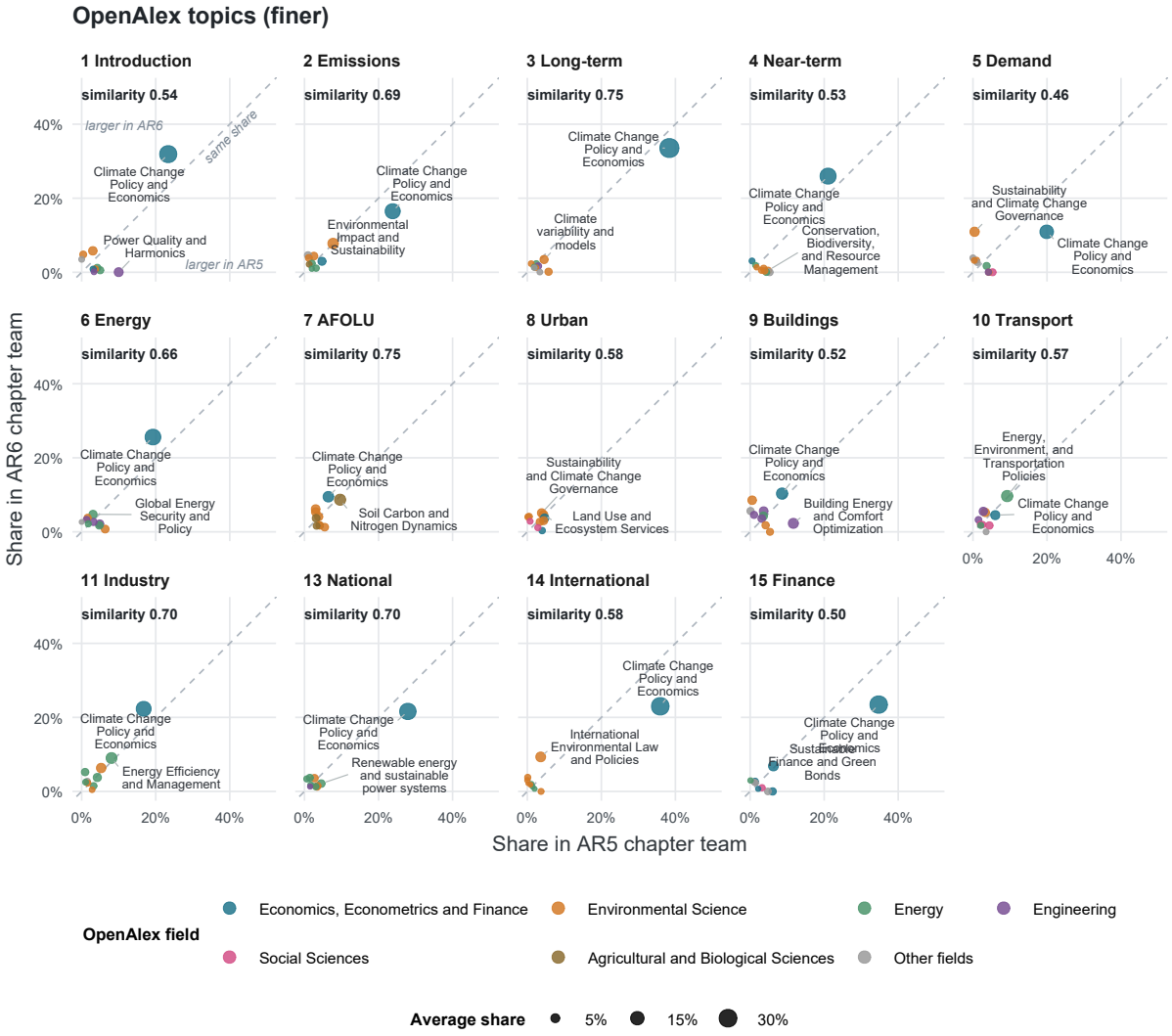


Figure S10: **Research profiles of the AR5 and AR6 chapter teams, OpenAlex topics.** As Fig. S9, at the finer level of OpenAlex topics.

Table S10: **Summary of the identification checks.** Percentage points; each of the 14 matched chapter pairs has equal weight. Brackets give 95% percentile intervals from resampling whole chapter pairs.

	All references	Published by 2013
Whole writing team (CLA + LA + CA)		
AR5 exiters (wrote AR5)	−7.5 [−8.6, −6.5]	−6.3 [−7.9, −4.8]
AR6 entrants (wrote AR6)	7.9 [6.1, 9.8]	5.7 [3.5, 8.2]
Adjusted AR6 own-team gap	6.1 [4.8, 7.5]	3.0 [1.0, 4.9]
Adjusted two-cycle contrast	15.2 [13.1, 17.4]	11.9 [9.4, 14.4]
Appointed lead authors (CLA + LA)		
AR5 exiters (wrote AR5)	−4.6 [−5.8, −3.4]	−3.3 [−5.0, −1.5]
AR6 entrants (wrote AR6)	3.6 [2.4, 5.0]	2.7 [1.3, 4.4]
Adjusted AR6 own-team gap	3.9 [2.8, 5.1]	1.6 [−0.3, 3.8]
Adjusted two-cycle contrast	8.0 [6.5, 9.7]	5.8 [3.8, 7.9]

Notes: Rows for exiters and entrants report the change in each group's share of its matched chapters' references from AR5 to AR6 (Figure S7). Gap rows subtract the mean gap under 9,999 size-preserving reallocations of authors within each pair.Comparisons with appointed experts who did not write the chapter are in Table S9.

S4 Paper-level selection models

Mainland China and other Global South-only papers. In the main models, Global South-only papers are a single category. That category combines two groups whose positions may differ: papers written entirely by authors at institutions in mainland China, and papers written entirely by authors elsewhere in the Global South. Table S11 therefore estimates the two groups separately, within the same models. Each coefficient is read as in the main table. It compares a paper with a Global North-only paper from the same choice set (same journal and year and, in columns 1 and 2, the same primary topic or subfield) that has the same prior citations, team size, international composition and AR6-author link. In the exact-topic specification, for example, the odds ratio of 0.43 means that a mainland China-only paper has 57% lower odds of being cited in AR6 than a comparable Global North-only paper on the same topic in the same journal and year.

The last row of the table compares the two Global South groups directly. It is the ratio of their odds ratios, tested within each model so that the correlation between the two estimates is taken into account. A value of 0.53 means that, holding the same covariates fixed, a mainland China-only paper has about half the odds of inclusion of an otherwise comparable Global South-only paper from another country. The contrast is clear when papers are matched on topic (0.53, 95% CI 0.33–0.86) or subfield (0.55, 0.33–0.91). It is weaker in the journal–year comparison (0.76, 0.57–1.01), where the interval just includes one.

The pattern across columns comes almost entirely from the other Global South-only papers. As the comparison narrows from journal and year to exact topic, their odds ratio rises from 0.48 to 0.81, and in the exact-topic model it is no longer distinguishable from one. Much of their lower inclusion within a journal therefore reflects the subjects on which they publish. The odds ratio for mainland China-only papers changes little, from 0.37 to 0.43, so their lower inclusion persists among papers on the same topic. The two groups look similar in the broad comparison because both are cited less within a journal. They differ in the narrow comparisons because only the second group's gap is largely a matter of subject.

These estimates describe differences in inclusion conditional on the covariates. They do not identify why the differences arise. Geography is measured by institutional affiliation, not by nationality or by the region studied. Topic matching captures subject only at the level of OpenAlex primary topics, and it reduces the sample to 696 cited papers. Differences in language, policy relevance or the specific questions assessed within a topic could all contribute.

Table S11: Paper-level correlates of selection, with Global South-only papers split by mainland China

	(1) Exact topic	(2) Exact subfield	(3) Journal–year
Prior citations (doubling of $1 + c$)	1.83*** [1.58, 2.11]	1.84*** [1.68, 2.02]	1.91*** [1.81, 2.03]
Global South only: mainland China (ref.: Global North only)	0.43*** [0.30, 0.63]	0.30*** [0.20, 0.46]	0.37*** [0.29, 0.47]
Global South only: other countries	0.81 [0.61, 1.08]	0.55*** [0.40, 0.75]	0.48*** [0.39, 0.59]
Mixed Global North–South team	0.76 [0.52, 1.10]	0.64*** [0.50, 0.82]	0.74*** [0.62, 0.87]
International author team	1.02 [0.85, 1.23]	1.08 [0.94, 1.25]	1.00 [0.92, 1.09]
Number of authors (doubling of $1 + n$)	1.04 [0.85, 1.27]	0.94 [0.78, 1.14]	0.84** [0.75, 0.94]
At least one AR6 author	3.15*** [2.43, 4.09]	3.99*** [3.07, 5.18]	5.45*** [4.50, 6.59]
Mainland China only vs. other Global South only	0.53** [0.33, 0.86]	0.55* [0.33, 0.91]	0.76 [0.57, 1.01]
Selected papers	696	1,303	3,370
Control papers	4,151	8,944	27,425
Choice sets	473	765	1,287
Journals	124	237	675
Choice-set fixed effects	Yes	Yes	Yes
Journal-clustered standard errors	Yes	Yes	Yes

Notes: Entries are conditional odds ratios with 95% confidence intervals in brackets. The dependent variable equals one when a paper is cited in AR6 WGIII. All comparisons are within publication journal and year; columns 1 and 2 additionally match on OpenAlex primary topic and subfield, respectively. Prior citations are accumulated through 2017, before the January 2018 author selection. Retained choice sets contain at least three controls per cited paper. Standard errors are clustered by journal. GN denotes Global North and GS Global South. Global South-only papers are split into papers whose authors are all affiliated with institutions in mainland China and all other Global South-only papers. The final row reports a within-model Wald contrast between these two coefficients; values below one indicate lower odds for mainland China-only than for other Global South-only papers. Samples are identical to those of the main paper-level estimates. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Matching rule or sample composition? The three specifications in the main table differ in two ways at once: the strata within which papers are compared, and the papers that enter the estimation. A choice set is retained only if the cited paper has at least three uncited papers in the same stratum. Tighter matching therefore keeps a smaller and different sample: 696 cited papers from 124 journals under exact-topic matching, against 3,370 from 675 journals under journal–year matching. To separate the two, I re-estimate all three specifications on the same 4,833 papers, the 693 cited and 4,140 control papers retained by the exact-topic design, so that only the strata change (Figure S11). On this common sample, the three specifications give nearly identical estimates. The odds ratio for a paper with an AR6 author is 3.14 under topic matching, 3.19 under subfield matching and 3.09 under journal–year matching.

For Global South-only papers it is 0.65, 0.64 and 0.65, and for a doubling of prior citations 1.82, 1.80 and 1.77. The larger author-link odds ratio and the wider geographic gap in the journal–year column of the main table therefore reflect the broader set of journals and papers that column covers, not the looser comparison. For a given set of papers, matching on topic or subfield in addition to journal and year changes the estimates little. The exact-topic estimates are the most conservative, but they describe papers in journals and topics where close comparisons exist, which is not a random subset of the literature.

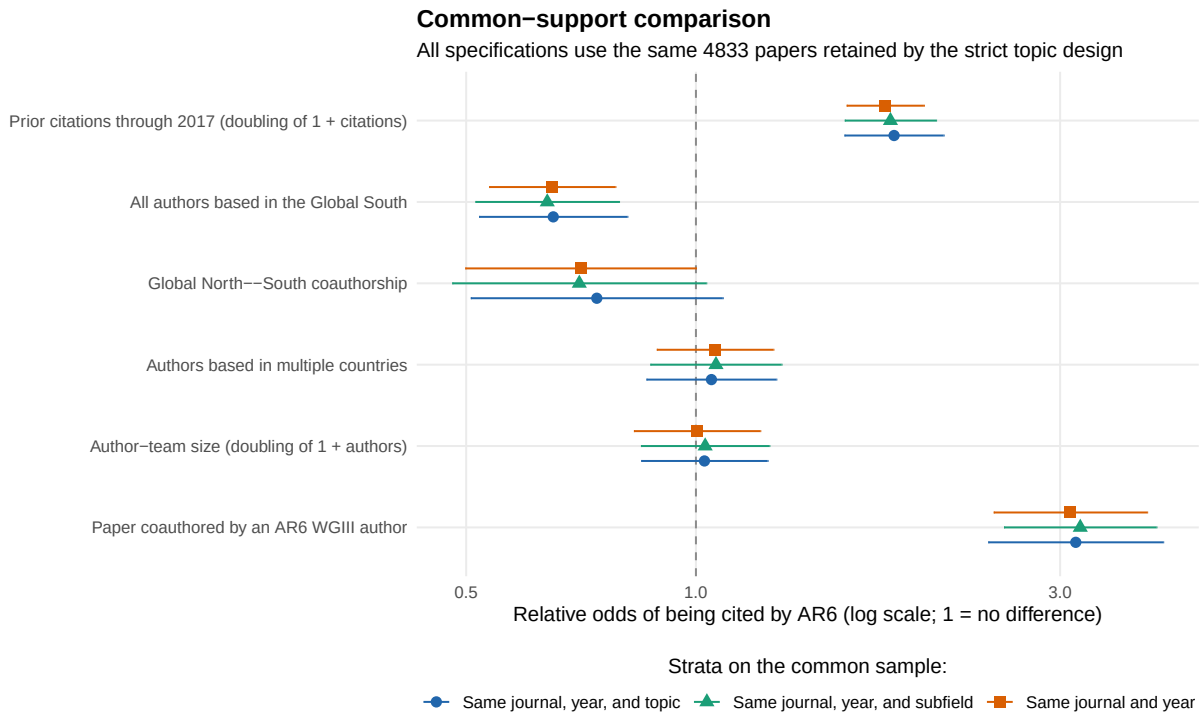


Figure S11: **Paper-level estimates on common support.** The three conditional-logit specifications use the same 4,833 papers (693 cited and 4,140 controls); only the choice-set strata change. Points are odds ratios and whiskers are journal-clustered 95% confidence intervals. This comparison separates the effect of changing the matching rule from the change in sample composition across the main specifications.

S4.1 Robustness: papers published after author selection

The main paper-level cohort ends in 2017 so that every paper, and its measured visibility, predates the January 2018 selection of the AR6 authors. Most of the turnover alignment, however, concerns work published from 2018 onwards (Table S8). As a robustness check, Table S12 repeats the role-split models for papers published in 2018–2021, with the same control sampling and matching rules. This cohort is not part of the main analysis because both the papers and their covariates postdate the appointments and are therefore potentially endogenous to them. Appointed authors may have written papers with the assessment in mind, steered their research towards the chapter scope, or attracted citations through their visibility as IPCC authors; any of these would strengthen the association between author links and inclusion without reflecting how the literature was selected. Prior citations, counted through 2021 because AR6 accepted papers until October 2021, accrue during drafting and may themselves reflect participation. Within each journal–year choice set every paper has the same exposure, but the estimates describe associations rather than selection on pre-appointment characteristics.

With these caveats, the results are consistent with the main cohort. The journal–year comparison contains 4,478 cited and 37,150 control papers. Odds ratios are 3.99–7.70 for papers with an appointed lead author and 4.59–4.96 for papers linked only to other credited participants, against 3.26–6.18 and 2.80–3.96 for 2012–2017. The lead-author odds ratio exceeds the other-credited one only in the journal–year model (ratio 1.55, 95% CI 1.20–2.01; $p = 0.43$ and $p = 0.25$ in the topic- and subfield-matched models). Prior citations (odds ratios 1.74–1.76 per doubling) and Global South-only authorship (0.32–0.43) are similar to or stronger than in the earlier cohort. The larger author-link odds ratios in this cohort are what the endogeneity concern would predict, so they should not be read as stronger evidence of selection.

Table S12: Robustness: paper-level correlates of selection for papers published in 2018–2021

	(1) Exact topic	(2) Exact subfield	(3) Journal–year
Prior citations (doubling of $1 + c$)	1.76*** [1.62, 1.91]	1.74*** [1.65, 1.83]	1.75*** [1.68, 1.83]
Global South only (ref.: Global North only)	0.43*** [0.34, 0.55]	0.32*** [0.26, 0.39]	0.35*** [0.31, 0.40]
Mixed Global North–South team	0.78 [0.57, 1.07]	0.61*** [0.50, 0.74]	0.66*** [0.57, 0.75]
International author team	0.88 [0.74, 1.06]	0.92 [0.82, 1.03]	0.99 [0.92, 1.06]
Number of authors (doubling of $1 + n$)	0.97 [0.85, 1.11]	0.89** [0.82, 0.96]	0.82*** [0.77, 0.88]
At least one appointed AR6 lead author (CLA or LA)	3.99*** [2.79, 5.72]	5.92*** [4.08, 8.60]	7.70*** [6.02, 9.83]
Other credited AR6 authors only	4.59*** [3.29, 6.40]	4.82*** [3.50, 6.64]	4.96*** [3.92, 6.28]
Selected papers	911	1,894	4,478
Control papers	5,585	13,795	37,150
Choice sets	584	1,023	1,287
Journals	148	288	737
Choice-set fixed effects	Yes	Yes	Yes
Journal-clustered standard errors	Yes	Yes	Yes

Notes: Entries are conditional odds ratios with 95% confidence intervals in brackets. The dependent variable equals one when a paper is cited in AR6 WGIII. All comparisons are within publication journal and year; columns 1 and 2 additionally match on OpenAlex primary topic and subfield, respectively. Papers were published in 2018–2021, after the January 2018 author selection; prior citations are accumulated through 2021, the year of the AR6 literature cutoff, and therefore overlap the drafting period. Papers and covariates postdate the appointments and are potentially endogenous to them; estimates are associations, not selection on pre-appointment characteristics.Retained choice sets contain at least three controls per cited paper. Standard errors are clustered by journal. GN denotes Global North and GS Global South. Appointed lead authors are Coordinating Lead Authors and Lead Authors. Other credited authors are Contributing Authors, Review Editors, chapter scientists, and editorial roles. A paper with any appointed lead author is coded as lead-linked, so the two indicators are mutually exclusive. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

S5 Journal abbreviations

Table S13: Supplementary Table: Journal acronyms and abbreviations

Acronym	Full Title	Abbreviation
Agric. Ecosyst. Environ	Agriculture Ecosystems & Environment	Agric. Ecosyst. Environ
AER	American Economic Review	Am. Econ. Rev.
Annu. Rev. Environ	Annual Review of Environment and Resources	Annu. Rev. Environ. Resour.
ApEnergy	Applied Energy	Appl. Energy
B&B	Biomass and Bioenergy	Biomass Bioenergy
B&E	Building and Environment	Build. Environ.
ClimPol	Climate Policy	Clim. Policy
ClimCh	Climatic Change	Clim. Change
COSust	Current Opinion in Environmental Sustainability	NA
ESSD	Earth System Science Data	Earth Syst. Sci. Data
Earth's Future	Earth's Future	Earth's Future
EcolEcon	Ecological Economics	Ecol. Econ.
Energies	Energies	Energies
Energy	Energy	Energy
EES	Energy & Environmental science	NA
EnBuild	Energy and Buildings	Energy Build.
EnEco	Energy Economics	Energy Econ.
EnEffic	Energy Efficiency	Energy Effic.
NA	Energy Journal	Energy J.
EnPol	Energy Policy	Energy Policy
Epro	Energy Procedia	Energy Procedia
ERSS	Energy Research & Social Science	Energy Res. Soc. Sci.
ERE	Environmental and Resource Economics	Environ. Resour. Econ.
EIST	Environmental Innovation and Societal Transitions	Environ. Innovation Societal Transitions
EnvPol	Environmental Politics	Environ. Politics
ERL	Environmental Research Letters	Environ. Res. Lett.
EnvScPol	Environmental Science & Policy	Environ. Sci. Pol.
EST	Environmental Science & Technology	Environ. Sci. Technol.
GCB	Global Change Biology	Global Change Biol.
NA	Global Change Biology Bioenergy	NA
GEC	Global Environmental Change	Global Environ. Change
GEP	Global Environmental Politics	Global Environ. Polit.
IEA	International Energy Agency	IEA
NA	International Environmental Agreements: Politics, Law and Economics	NA
IJGGC	International Journal of Greenhouse Gas Control	Int. J. Greenhouse Gas Control
IJHE	International Journal of Hydrogen Energy	Int. J. Hydrogen Energy
Joule	Joule	Joule
JClePro	Journal of Cleaner Production	J. Cleaner Prod.
JEEM	Journal of Environmental Economics and Management	J. Environ. Econ. Manage.
JEM	Journal of Environmental Management	J. Environ. Manage.
JIndEcol.	Journal of Industrial Ecology	J. Ind. Ecol.
MASGC	Mitigation and Adaptation Strategies for Global Change	Mitigation Adapt. Strategies Global Change
Nature	Nature	Nature
NCC	Nature Climate Change	Nat. Clim. Change
NatCom	Nature Communications	Nat. Commun.
NatEn	Nature Energy	Nat. Energy
NatGeo	Nature Geoscience	Nat. Geosci.

Table S13: Supplementary Table: Journal acronyms and abbreviations *(continued)*

Acronym	Full Title	Abbreviation
NatSust	Nature Sustainability	Nat. Sustainability
OECD	Organisation for Economic Co-operation and Development	OECD
OneEarth	One Earth	One Earth
NA	Philosophical Transactions of the Royal Society b: Biological Sciences	Philos. Trans. R. Soc. B
NA	Philosophical Transactions of the Royal Society a: Mathematical, Physical, and Engineering Sciences	Philos. Trans. R. Soc. A
PlosOne	PLoS One	PLoS One
PNAS	Proceedings of the National Academy of Sciences of the United States of America	PNAS
RSER	Renewable and Sustainable Energy Reviews	Renew. Sustain. Energy Rev.
RenEne	Renewable Energy	Renewable Energy
ResPol	Research Policy	Research Policy
REE	Resource and Energy Economics	Resour. Energy Econ.
ResConRec	Resources, Conservation and Recycling	NA
REEP	Review of Environmental Economics and Policy	Rev. Environ. Econ. Policy
RECIEL	Review of European, Comparative & International Environmental Law	Rev. Eur. Comp. Int. Environ. Law
Science	Science	Science
Sci. Total Environ.	Science of the Total Environment	Sci. Total Environ.
SR	Scientific Reports	Sci. Rep.
Sust.	Sustainability	Sustainability
SustSc	Sustainability Science	Sustainability Sci.
SCS	Sustainable Cities and Society	Sustainable Cities Soc.
TechFore	Technological Forecasting and Social Change	Technol. Forecast. Soc. Change
Transp. Res.A	Transportation Research Part A Policy and Practice	Transp. Res. Part A Policy Pract.
Transp. Res.D	Transportation Research Part D Transport and Environment	Transp. Res. Part D Transp. Environ.
NA	Wiley Interdisciplinary Reviews: Climate Change	WIREs Clim. Change
WorldDev	World Development	World Dev.
JPubE	Journal of Public Economics	J. Public Econ.
JPE	Journal of Political Economy	J. Political Econ.
QJE	Quarterly Journal of Economics	Q. J. Econ.
NA	Food Policy	Food Policy
NA	Transport Policy	Transp. Policy
NA	Transport Reviews	Transp. Reviews
NA	Climate Change Economics	Clim. Change Econ.
JEP	Journal of Economic Perspectives	J. Econ. Perspect.
EER	European Economic Review	Eur. Econ. Rev.
JEL	Journal of Economic Literature	J. Econ. Lit.
NA	Natural Resources Forum	Nat. Resour. Forum
ReStat	Review of Economics and Statistics	Rev. Econ. Stat.
Biofpr	Biofuels Bioproducts and Biorefining	Biofuels Bioprod. Biorefin.
ESR	Economic Systems Research	Econ. Syst. Res.
JEEP	Journal of Environmental Policy & Planning	J. Environ. Policy Plann.