Geographical disparities in navigating rejection in science drive disparities in its file drawer

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Abstract

Scientific progress relies on making research contributions public, typically through journal publication, enabling others to build on them. However, publishing often requires overcoming one or more rejections. This study examines how scientists' differential responses to manuscript rejection shape both published knowledge and the "file drawer" of unpublished research. Analyzing 126K manuscripts rejected by 62 STEM journals published by the Institute of Physics Publishing, we document several new empirical facts. Controlling for manuscript quality (proxied by peer review recommendations) and comparing authors from Western and non-Western countries, we find that authors based in Western countries are 5.9% more likely to publish rejected manuscripts elsewhere, publish 25 days faster, revise 6% less, and change co-authors 11.6% less. A plausible contributing mechanism is geographic differences in access to *procedural knowledge* – how to interpret feedback from these journals, revise, and resubmit elsewhere. Although exploratory surveys of rejected authors are inconclusive, we find that post-rejection outcomes are better for corresponding authors with prior publishing experience and Western co-authors, both of which may proxy procedural knowledge. These findings imply that the "file drawer" contains a disproportionate number of ideas from non-Western countries, partly due to disparities in procedural knowledge.

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The authors declare no conflict of interest.

Significance statement

Many valuable contributions to science are initially rejected and some end up unpublished ("in the file drawer"). We study which scientists are able to avoid the file drawer by tracking the outcomes of 126k manuscripts rejected by 62 STEM journals. Controlling for submission quality with peer reviewer recommendations, we find that relative to authors at institutions in Western countries, those in non-Western ones are less likely to publish, take longer to publish, revise more, and change co-author teams more. These disparities may be affected by differential access to the "procedural knowledge" of publishing, such as how to interpret feedback, and revise and resubmit. How scientists navigate rejection is an important determinant of disparities in the impact of ideas from different countries.

1. Introduction

Rejection is ubiquitous in many creative domains, and science is no exception. For example, rejection rates at scientific journals can be as high as 93% (*Science*), most academic job applications do not yield offers (1), and funding agencies like the U.S. National Institutes of Health (NIH) reject about 80% of grant proposals (2). When rejected manuscripts and ideas are abandoned they are said to end up in science's "file drawer" of unpublished research (3). The size of the file drawer can be substantial. For example, in a sample of 328 manuscripts rejected from International Journal of Radiation Oncology, Biology, Physics during 2010 and 2012, 71.7% were ultimately published in PubMed-listed journals, leaving 28.3% of manuscripts in the file drawer (4). Meanwhile, tracking pre-registered trials in the social (5) and medical sciences (6) shows that only 43% and 27% resulted in publications, respectively.

Science rejected on the grounds of low quality is, arguably, best relegated to the file drawer. However, the historical record shows that many initially rejected contributions eventually became highly impactful. A number of manuscripts that were rejected, resubmitted, and ultimately accepted have been recognized with Nobel prizes (7–9). Such outcomes depend upon scientists displaying persistence, tenacity and *resourcefulness* in the face of rejection. For example, in the early 1920s, the Indian physicist Satyendra Nath Bose resolved an open problem in quantum physics – how to derive Planck's law from first principles (10). Bose sent the paper to the journal *Philosophical Magazine*, but never heard back. Undeterred, Bose sent a slightly revised version of the paper to Einstein, who immediately appreciated its merit, translated it, and with Einstein's endorsement the paper was published in *Zeitschrift für Physik*. The cross-pollination of ideas between Bose and Einstein eventually resulted in the discovery of a new state of matter, Bose-Einstein Condensates. Of course, many cases of rejection do not realize such impact. For example, in 1892, Lord Rayleigh was surprised to discover a manuscript by John James Waterston that developed the kinetic theory of gasses well before Maxwell, who was ultimately credited for the theory. The author and the manuscript were obscure because when Waterston submitted it to the Royal Society, a reviewer concluded, "The paper is nothing but nonsense, unfit for reading before the Society" (11).

Evidently, navigating rejection successfully, and resubmitting rejected (or ignored) but good ideas is critical for the growth of knowledge. Bose's case also illustrates that navigating rejection is aided by what we call "procedural knowledge" – understanding how to interpret rejections (12–14), revise, and resubmit for consideration by others. What would have happened to Bose's contribution had he over-interpreted the silence from *Philosophical Magazine* or lacked access to experienced insiders like Einstein?

Bose's case raises the concerning possibility that the ability to navigate rejection, and procedural knowledge in particular, is distributed unevenly around the globe. To the extent that there are geographical differences in navigating rejection, publicly visible contributions will not mirror the privately known "intended" or "potential" contributions. Such patterns could be consequential for knowledge accumulation. Researchers make choices such as which topic to pursue or how to interpret data based in part on the choices of others, and if others' choices are not visible then the choices shaping future work are not fully informed. Furthermore, if the research from a particular region is disproportionately unpublished or published less prominently then not only would those authors' careers be set back, but the topics relevant to that region will be less likely to be pursued

by others (15). Biases in the geographical composition of the evidence base may also bias researchers' theories (16). To the extent that such disparities are caused by differences in procedural knowledge, they are relatively amenable to policy interventions, such as training sessions and open seminars.

In this paper we focus on differential responses to manuscript rejection. We propose that authors from Western countries, which we define here as those affiliated with institutions (self-reported during submission) located in North America, Europe, and Oceania, have better access to procedural knowledge about publishing in outlets based in those countries than authors from non-Western countries. This better access may come from closer geographic and social proximity to editors, who are often based in Western countries (17–19), and colleagues and professional networks of contacts who frequently publish in these outlets (20). If this hypothesis is valid, then rejected manuscripts from authors in Western countries should have better post-rejection outcomes compared to those from non-Western authors, such as getting rejected manuscripts ultimately published and doing so quicker. Consequently, we pose the following research questions:

1) Do authors from Western and non-Western countries experience different publishing outcomes after initial manuscript rejection? and

2) Are these disparities, if any, related to differences in procedural knowledge in navigating the rejection?

Evidence on these questions is limited, although some related literatures are extensive. Studies on geographic disparities in publishing generally find that research from authors in non-Western countries receive fewer citations and are less likely to be published in prominent outlets (21–23). These disparities have been linked primarily to unequal access to the resources and capabilities (including fluency in English) needed to produce high-quality research for prominent English-language outlets (24–26), biases of editors and reviewers (18, 27, 28), and biases of the audiences (29, 30). However, geographic differences in the revision and resubmission process have not been extensively considered (31).

Studies exploring individual-level variation in how scientists respond to rejection are few, but they suggest that the variation is large and important. For example, data from Dutch funding competitions shows that rejections causally and durably affect scientists' subsequent fundraising success (32). Biomedical scientists who barely lost out on NIH funding were 12.6% more likely to permanently cease NIH-related research, yet some had better-than-expected research trajectories (33). Studies of publishing and science more generally provide suggestive evidence of procedural knowledge as a driving mechanism. Sekara and colleagues demonstrate that publishing in top journals for the first time is increasingly associated with having a co-author who has published in those journals in the past (34). Even more suggestive is the evidence of Kolympiris et al., who find the fundraising performance of researchers increases after a colleague returns from working at the NSF (35). Albeit not measuring procedural knowledge directly, these studies are consistent with it helping scientists successfully navigate formal evaluations and the inevitable rejections.

We address our research questions by studying post-rejection outcomes and aspects of procedural knowledge directly, using large-scale administrative peer review data from the Institute of Physics Publishing (IOP), one of the world's largest STEM publishing companies. The data comprise 126K rejected submissions from 62 peer reviewed journals. We identify whether, when, and where these rejected manuscripts were eventually published, and how these outcomes vary by (self-reported) author geography. We use the evaluations of peer reviewers when the papers were rejected to proxy for perceived submission quality, enabling us to rule out the most plausible confounder. We find that authors from Western countries are 5.9% more likely than those from non-Western countries to ultimately publish rejected papers. Among rejected papers that do achieve publication elsewhere, and after controlling for submitted manuscript quality and other plausible confounders, Western authors publish in more prestigious venues, approximately 25 days faster, revise the manuscripts 6% less, and are 11.6% less likely to change the authorship team. Ultimately, papers of Western and non-Western authors ended up in journals with similar impact factors and received similar amounts of non-self citations. Overall, Western authors experience better post-rejection outcomes than non-Western authors even when their initial rejection decisions indicate similar quality and, presumably, future publishing prospects.

These results document, to our knowledge for the first time, that post-rejection outcomes differ substantially by author geography. An intuitive and common explanation of these results is that they are caused by differences in research quality and evaluator bias (18, 25, 27). Crucially, our research design helps rule these explanations out. First, research quality and bias should be reflected in peer reviewer recommendations from the rejecting journals, and we find post-rejection differences conditioning on these recommendations. Second, we analyze editor decisions conditional on reviewers' recommendations, and find that editors are slightly more favorable towards Western authors, which should make our estimates of gaps in outcomes of *rejected* papers conservative.

Although controlling for the perceived quality of manuscripts helps rule out commonly studied mechanisms, it does not by itself *rule in* the mechanism of procedural knowledge. To test our procedural knowledge argument more directly, we conduct two more analyses. First, we assess how post-rejection outcomes vary with authors' prior publishing experience and the presence of Western co-authors, both of which are likely to correlate with levels of procedural knowledge. We find that authors with more experience and more Western co-authors have better post-rejection outcomes.

Second, we analyze data from a survey of rejected authors that provides insights on two aspects of procedural knowledge – interpretation of rejection feedback and strategy for next steps. Survey responses do not show substantial variation by author geography, although the sample of respondents was small and had a low and non-random response rate. Further research is needed to identify which dimensions of procedural knowledge, if any, drive the differences in outcomes.

Overall, our study offers several contributions. First and most importantly, we document substantial geographical disparities in post-rejection outcomes among manuscripts of similar quality. To our knowledge this is the first study to find that non-Western authors are much more likely than Western ones to end up in the file drawer after rejection and, even when avoiding the file-drawer, they take longer to publish, and revise content and adjust authorship teams more.

These post-rejection disparities represent a novel mechanism generating geographical disparities in scientific representation and impact.

Second, we provide evidence that suggests differential access to procedural knowledge may contribute to differential post-rejection outcomes. Specifically, author teams with plausibly more procedural knowledge, via either prior publishing experience and/or more Western-country coauthors, had better post-rejection outcomes. Analyzing survey responses of rejected authors suggests that the key aspect of procedural knowledge is neither interpretation of rejections or next-step intentions. Therefore, we speculate that other aspects of procedural knowledge, such as appealing decisions, selecting appropriate subsequent outlets, and converting intentions into actions, are key.

Last, the results help better contextualize existing evidence. Prior work on the geographical representation in published research focuses on biases in the peer review process, downplaying the possibility that authors can resubmit rejected papers. Even if bias against some group of authors exists, in principle they may resubmit until they find a bias-free outlet or the variability of peer review evaluations favors them. So, their research would see the light of day, albeit with a delay. Empirically, we find some support for this argument. Of all submissions to the journals that we study, Western authors' manuscripts are accepted by the initial journal of submission at a 24.6% higher rate than those of non-Western authors. However, when examining whether the submissions were ultimately published *somewhere,* including in journals outside our sample, the Western-non-Western publication gap decreases to 12.9%. Consequently, accounting for resubmission somewhat decreases (but does not completely mitigate) the disparities in peer review outcomes of particular outlets that prior work has documented.

2. Related Literature

Rejection in scientific publishing

Scientists typically make their findings visible through publishing. As the volume of papers continues to grow, approaching 3 million papers per year (36), there is a corresponding growth in rejection counts. Many outlets reject more than 60% of submissions and a typical manuscript can take two or more resubmissions before publication (37).

The journey of getting research published usually extends beyond a single submission attempt that ends in an acceptance or rejection. Typically, after rejection authors (possibly revise and) resubmit their manuscripts to another outlet (38). Alternatively, authors may abandon the project. Cases of abandonment are common: a study tracking conference paper submissions found that two thirds of abstracts presented at one medical conference remained unpublished even after five years (39). Similarly, investigations into the fate of manuscripts rejected by specific journals have found that only about 54% to 76% are eventually published elsewhere (4).

While it is arguably most consequential for science (and authors) whether the paper is ultimately published or abandoned, the time and effort expended on revising and resubmitting it, as well as the prestige of the publishing venue, may also have significant consequences. Previous studies show it can take multiple years from rejection to publication (40, 41). Most authors tend to

resubmit to venues with the same or lower impact factor with higher chance of success as well (42, 43).

Overall, these prior works establish that post-rejection outcomes vary substantially across researchers, but the source of variation remains unclear. In particular, it also remains to be examined if authors from different regions have systematically different outcomes.

Procedural knowledge in navigating scientific institutions

We hypothesized that one way in which author geography matters is that it is associated with access to procedural knowledge, which we define as knowledge of the tacit norms and rules needed to successfully navigate ostensibly straightforward and meritocratic institutions. Given its unwritten form, this knowledge is usually acquired through direct experience or from knowledgeable mentors, such as experienced individuals in one's professional network (20, 34, 35). Less access to this knowledge would lead to poorer ability to navigate the institution, which in our setting would mean poorer outcomes after rejection.

It is plausible that authors from Western and non-Western countries would have differential access to procedural knowledge. First, many good sources of procedural knowledge, such as editors, conferences, and publishing companies, are located in Western countries (17, 19, 40). Geographical distance and legal barriers may make it more difficult for non-Western authors to access these sources. Additionally, the research of Western authors tends to be overrepresented in many top outlets (44), which enables their local colleagues to indirectly access their direct procedural knowledge.

Existing research provides suggestive, albeit indirect, evidence of the advantages that procedural knowledge provides. For example, Sekara et al. (34) suggest that co-authoring with researchers who have previous publishing experience can lead to a higher chance of acceptance, likely due to their familiarity with journal intricacies. The study that comes perhaps closest to establishing the role of procedural knowledge is Kolympiris et al., which finds that colleagues of researchers who spent time working in the U.S. National Science Foundation have better fundraising performance after those researchers return to their institutions, presumably bringing procedural knowledge with them (35). Lastly, Shastry and Shurchkov examine one key aspect of procedural knowledge – interpreting rejection feedback. They find that, overall, economists of different genders interpret feedback similarly, although there are statistically significant differences among junior scholars, with female economists interpreting identical feedback more negatively (14).

We fill the gaps in these literatures by, first, examining how post-rejection outcomes vary by author geography. The main outcomes we focus on is whether a rejected paper is ultimately published. Additionally, for those achieving publication, we focus on how quickly it was achieved, the change in outlet prestige between that rejecting vs. publishing the paper, and how much authors revised the paper and changed their authorship team. These analyses aim to establish empirical facts about geographic disparities in post-rejection outcomes.

Given the importance and potential variation in how individuals learn from rejection (12–14, 33), we then analyze data from a survey to probe how authors from different regions interpret similarly enthusiastic reviewer feedback. Additionally, prior work has found differences in

project choice and submission strategy across author seniority levels (45), potentially related to tenure-related incentives (46, 47). Given the wide variety of incentive structures and norms across global scientific communities, we use the survey to probe author resubmission and revision strategy. Our goal with this author survey analysis is to identify mechanisms that can plausibly account for the empirical facts established by the archival analysis of manuscripts.

3. Data and Methods

Peer review data

We analyze administrative peer review data from the Institute of Physics Publishing. The data include submission and peer review metadata from 62 journals in the physical sciences, covering 203K unique manuscripts submitted from 430K authors during 2018-2022 (See Supplementary Information S1). 62.0% (126K) of these submissions were rejected, which is our focus.

We classify the geographical region of each manuscript based on the self-reported country of the corresponding author. During submission, authors could choose only one country, so we assume they chose their primary one. In the 0.99% of cases in which there was more than one corresponding author, we focused on the one listed last. We focus on the corresponding authors on the assumption that these individuals are most responsible for manuscript's submission and revision decisions. Their self-reported country is assumed to reflect the authors' resources, external incentives, professional networks, and therefore their publication practices.

For the 152 unique countries in our dataset, we group them into 12 major regions according to the UN geoscheme, with Oceania referring to Australia and New Zealand. We further aggregate the regions into Western countries and non-Western countries, where Western countries are those in North America, Europe, and Oceania and non-Western countries are in Africa, Asia, and Latin America and the Caribbean (hereinafter referred to simply as Latin America for brevity). In the dataset submissions to our journal set from non-Western authors comprise 70.9% of all submissions and 79.3% of all rejections (See Table S4 for number of submissions from each country).

Post-rejection outcomes: published or not

Our main outcome is whether a rejected submission was ultimately published. We identify rejected-and-published submissions as follows. We utilize OpenAlex, a comprehensive bibliometric database with larger coverage than common competitors (48). First, we linked all authors of submitted papers to their OpenAlex records. Linkage was done using either ORCID, if provided during submission, or through searches based on author name (see Supplementary Information S2 for details on ORCID-based and name-based searches). To maximize search recall and account for potential errors in name disambiguation, we took a liberal approach, linking authors to all matching records in OpenAlex, on the assumption that any one of them might contain the true rejected-and-published-elsewhere paper. Using ORCID-matched records as a reliable benchmark, we estimated the overall recall rate of our author-linking approach to be 0.82 (See Supplementary Information S3 for matching statistics).

Second, we used the OpenAlex author records to generate a list of all papers the authorship team published after the date of rejection. If the rejected submission is ultimately published, it should

appear in this list. Note that this list of candidate publications requires only *one* author on the team to have *one* correctly linked record for the correct paper to appear in this list. Considering this, recall improves with larger authorship teams and accounting for the team size distribution, we estimated an overall recall rate for paper matching based on author matching to be approximately 0.97 (See Supplementary Information S2 for calculation details).

Third, we identified the rejected-and-published paper among candidate publications. Identifying which published paper corresponds to a rejected one can be subjective, particularly for papers that underwent substantial revision: presumably, a project may be revised so much that it is more appropriately considered a distinct project rather than a continuation of the rejected one. To address this issue we relied on authors' *self-reports* from the survey of which rejected paper corresponds to which published one. We used these self-reported rejected-published paper pairs to train a logistic classifier to identify the published version, if it exists, among the candidate list. Note that survey respondents were not instructed on how to decide whether an ultimately published paper is the same project as the rejected one. The classifier uses similarity between the rejected and candidate paper pair in authorship lists, title, and abstract. It achieved a 0.97 precision and 0.78 recall in successfully identifying the publication version. Details of the training procedure and performance metrics are discussed in Supplementary Information S3.

OpenAlex and other bibliometric databases have inclusion criteria that can underrepresent works from certain geographical regions (49). An important concern for our research design is that any observed geographical disparities in whether rejected papers are ultimately published might be confounded with disparities in OpenAlex indexing. One factor that mitigates this concern is that the rejected papers we study were *submitted* to English-language journals indexed by OpenAlex. It is therefore likely that publishing in such outlets was a priority for the authors, and they are likely to resubmit papers to similar outlets after rejection, which would also likely be indexed. Second, we test for this concern using the survey data, by measuring whether the papers authors identify as the ultimate publications are indexed in OpenAlex, and whether the rate varies by author region.

Post-rejection outcomes: prestige, time, revising effort, authorship change and citation

For manuscripts we are able to link with ultimate publications, we also examine four additional publication outcomes: journal prestige, time interval to publication, extent of revisions in abstract text, change in authorship composition and citation gain. We evaluate journal prestige by Impact Factor[1] of the journal that ultimately accepted it. We measure publication intervals in days by the time elapsed from the date the rejection decision is made to the eventual publication date. The revision of the abstract text is quantified by the edit distance, which measures the minimum operations required to revise the original abstract of the rejected version to the final published version. Authorship team changes are measured by the likelihood of authors being added or removed from the publication. Citations are collected as the number of citing papers within the first two years of publication. See Supplementary Information S7 for outcome distribution and S9 for alternative measures.

[1] Impact Factor, as calculated by OpenAlex for 2023, is the average number of citations research papers received within two years.

Accounting for submissions' expert-perceived quality

Not all rejections are the same: some rejected papers may be close to the bar for acceptance and others far from it. Consequently, examining post-rejection outcomes without adjusting for the quality of the submission can lead to confounded interpretations. For instance, Western authors may have higher rates of ultimate publication not because of greater procedural knowledge but because of higher-quality submissions.

We account for submissions' quality, as perceived by experts, by constructing a vector "*Perceived Quality*" combining three pieces of information: the rejecting journal, the number of peer review rounds (with 0 indicating desk rejects), and the set of peer review recommendations in the last round of review. The review recommendation is aggregated at four levels of positivity: "reject", "reject and resubmit", "revise", and "accepted", which is numerically scored from 1 to 4 (See Supplementary Information S5 for detailed categorizations). An example of such a vector is shown in Figure 1 below.



Fig. 1*. Illustration of Perceived Quality, a categorical variable composed of the rejecting journal, number of peer review rounds and set of review feedback positivity scores in the last round of review. The example indicates a submission that got rejected at journal "2D Materials" after one round of review and at the first/last round received one review recommendation of "Revision" and two review recommendations with "Rejection."*

The distribution of submissions across review rounds and review recommendations for Western and non-Western authors is shown in Table S5. Approximately two-thirds of the rejected manuscripts are desk rejected: 23.8% of submissions from Western authors and 50.7% from non-Western ones. Fewer than 3% of manuscripts are rejected after undergoing two or more rounds of peer review.

Reviewer recommendations incorporate both the intellectual merit of the submission and the potential biases and noise inherent in the review processes. A more positive *Perceived Quality* — indicating more rounds of review and favorable recommendations, whether due to the merit or bias — should predict the paper being published elsewhere if resubmitted. This is the case empirically. For example, the ultimate acceptance rate for submissions rejected after one round of review is 62.0%, but 95.6% after the second round. This supports the interpretation of *Perceived Quality* as a proxy of merit and/or bias that is characteristic of the entire field rather idiosyncratic to IOP journals.

For potential biases in the construct of "expert-perceived quality", we test whether any bias influences editors' decisions regarding rejection, revision, or acceptance. We find suggestive evidence that conditional on reviewers' recommendations, editors were 2.1% more likely to Revise/Accept vs. Reject submissions from Western authors. Pro-Western biases among editors in acceptance should make post-rejection outcomes weaker for Western compared to

non-Western authors. If empirically we find the outcomes to be stronger than for non-Western authors, the gap is likely conservative (See Supplementary Information S6 for the editor bias results and an elaboration of the argument for conservatism).

In the analyses below we study reviewed-and-rejected and desk-rejected submissions together, but, for robustness, we repeat the analyses with the reviewed-and-rejected subset of 43k submissionand find qualitatively similar results (see Supplementary Information S8 and Table S11 for results).

Model specifications

We use OLS regressions to measure the associations between author geography and post-rejection publishing outcomes, specified as follows:

$$Publishing.Outcome_i = \beta_0 + \beta_1 If.Western_i + \beta_2 Author.Seniority_i + \beta_3 Author.Gender_i + \beta_4 Team.Size_i + \sum_j \beta_{5,j} Month_j + \sum_k \beta_{6,k} Perceived.Quality_k + \epsilon$$

The key publishing outcome is whether the paper is eventually published, "*If.Published*", an indicator variable that equals 1 if the manuscript is published after rejection and 0 otherwise. For manuscripts that are published, the publishing outcomes also include prestige, time to publication, amount of revision and authorship team changes.

The focal independent variable is the indicator "*If.Western*", which is an indicator representing whether the corresponding author is from a Western country. For finer-grained analyses by region, we replace this variable with indicators representing the 12 regions. Additionally, we control for a several factors that may be related to publishing outcomes through mechanisms that are not the focus of the paper: (a) "*Author.Gender"*, the self-reported gender of the corresponding author; (b) "*Author.Seniority*", the seniority of the corresponding author, proxied by the number of previous publications by the time of rejection; (c) "*Month*" of rejection, a categorical variable with 68 levels; (d) "*Team.Size*", the number of authors in the authorship team. We also use indicators of "*Perceived.Quality*" to control for expert-perceived quality. For descriptive statistics of independent and outcome variables and alternative regression specifications, see Supplementary Information S7.

Survey

We conducted a survey with two goals. First, we use it to construct and validate the key dependent variable – whether a rejected paper was ultimately published. We asked authors to provide links to their rejected-and-published-elsewhere papers and trained a classifier on these data to then identify published-elsewhere papers for other rejected submissions (See Supplementary Information S3 for data collection and classifier training). Second, we directly test the procedural knowledge hypothesis by probing for geographical differences in how authors interpret rejection decision letters and strategize next steps. For interpretation, we ask how authors perceived the negativity and fairness of the decision letter. For strategy, we ask for the

authors' next publishing decision after rejection and the extent of effort and resources allocated to revisions.

We selected a stratified random sample of 10,000 corresponding authors whose papers were rejected, oversampling those from manuscripts that underwent peer review, manuscripts from Western countries, and manuscripts that were not published. The survey instrument and sampling method are presented in Supplementary Information S10.

There were 218 out of 287 responses that could be successfully linked to the submissions in our dataset. 106 respondents provided links to rejected-and-published publications, allowing us to collect their authorship, title and abstract information. Western authors responded at higher rates relative to non-Western ones (62% of the respondent group and 38% of the non-respondent group were Western authors). Characteristics of the respondents are presented in Table S16.

4. Results

Geographical gap in post-rejection publishing outcomes

First, we examine geographical differences in publication outcomes among rejected papers, controlling for their expert-perceived quality and other key characteristics. Figure 2 shows regression estimates of geographical differences in the probability that rejected papers are ultimately published. The papers are grouped into twelve regions, with those in orange indicating Western countries and blue indicating non-Western ones. Panel A shows that authors from non-Western countries are less likely to ultimately publish their paper. For instance, Southern European authors publish 70.7% of their rejected works, while Eastern Asian authors publish only 60.0%. However, there is intra-region variation. Japan, for example, is an exception to the generally lower publication rates in East Asia with one of the highest publication rates among all countries (See Supplementary Information S4 for country-level publication rates). Overall, for arguably the most important outcome—making rejected papers visible—Western authors have 5.9% ($P < 0.001$) more success (See Table S8 and S10 for regression results with and without control). Panel B shows that these results are not confounded by more recently rejected papers having less time to be published: the geographical gap appears across all months of rejection.

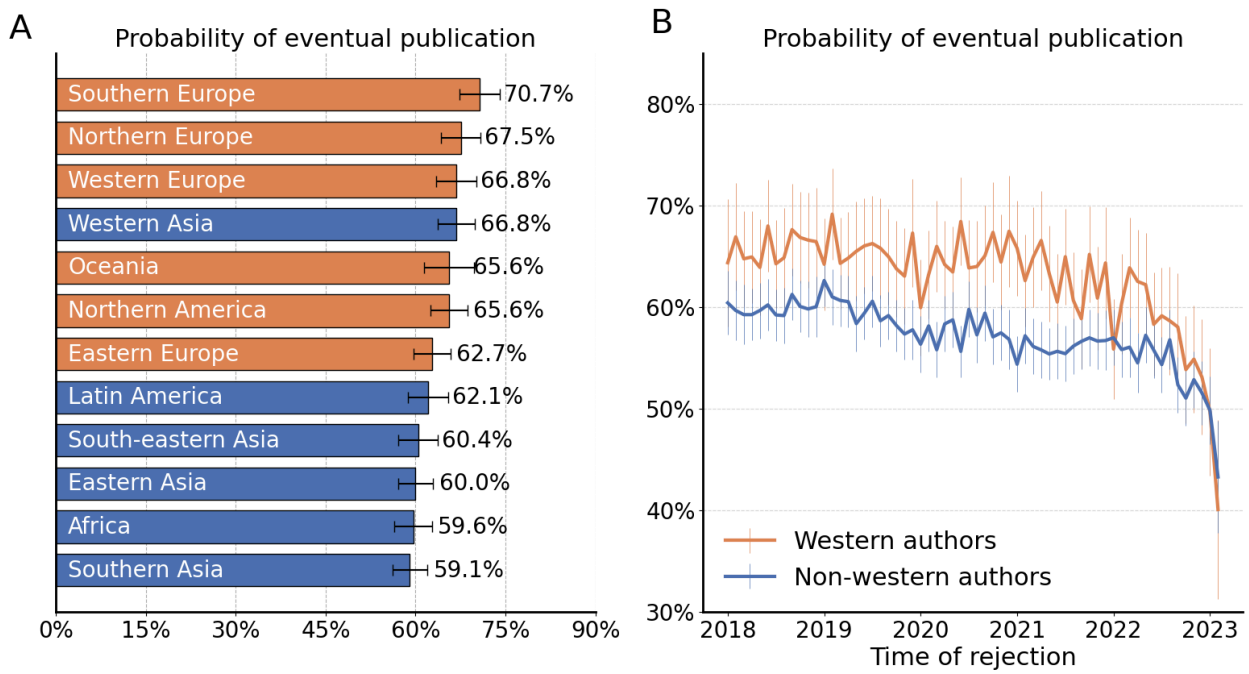


Fig. 2. *Coefficient estimates from regressions predicting ultimate publication. The models control for manuscripts' perceived quality and other key attributes. (A) authors from Western regions (in orange) show an overall higher chance of post-rejection publication than authors from non-Western regions (in blue). (B) Submissions with earlier rejections are more likely to be found published in 2024. Western-country authors exhibit consistently higher publication rates across the months of rejection. The regression coefficients are displayed relative to the reference category: a submission to the "Journal of Physics D: Applied Physics," desk-rejected in January 2018, with the corresponding author of unknown gender.*

Next, we focus on the set of rejected papers that was ultimately published. Figure 3 shows that, in the raw data, rejected papers are published in lower-impact factor journals on average for authors from all regions. In our sample, Western authors tend to submit to IOP journals with higher impact factors and, when publishing after rejection, experience large drops in prestige between rejecting and publishing venues (difference=-0.76, $P < 0.001$). Non-Western authors submit to IOP journals with relatively low impact factors and experience a much smaller drop in prestige (difference=-0.60, $P < 0.001$). Using the regression model specified as above, with the ultimate impact factor as the dependent variable and rejecting impact factor as a control, we find that non-Western authors ultimately publish in journals with 0.17 ($P < 0.001$) higher impact factors than Western authors (See Supplementary Information S9 for regression specification and Table S13 for results).

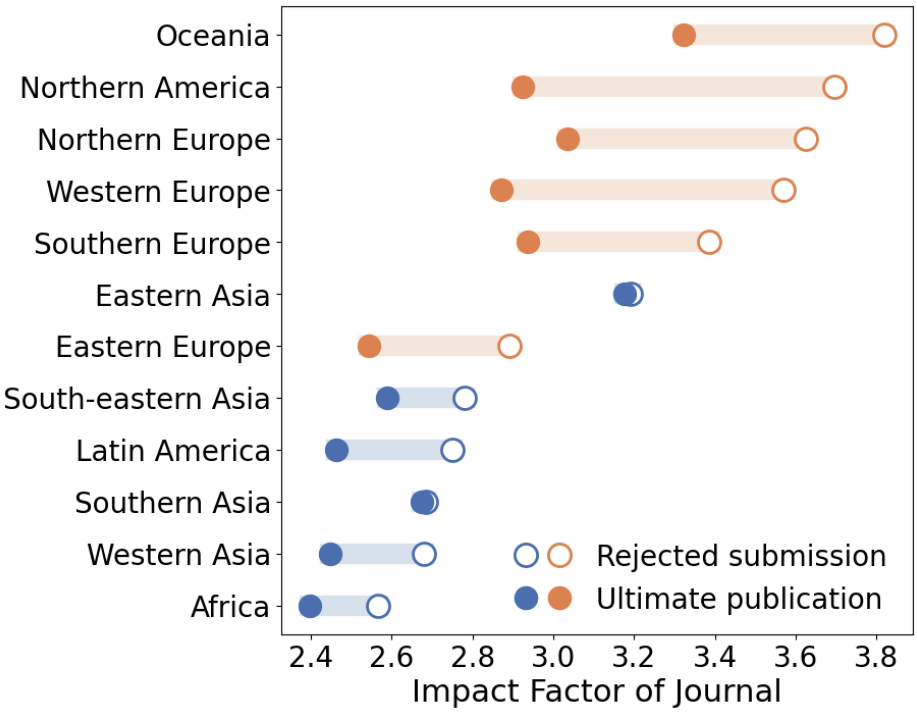


Fig. 3. *Raw data showing the prestige of journals submitted to and rejected (open circles) and those ultimately publishing the submissions (solid circles) across regions. Authors from Western countries (orange) tend to submit to higher-prestige journals than non-Western authors (blue) and experience a notable drop in journal prestige upon rejection. Nevertheless, submissions by Western authors tend to be ultimately published in journals with slightly higher prestige than those by non-Western authors.*

Focusing on the other key outcomes for those rejections resulting in an ultimate publication, we find that compared to non-Western authors, Western ones publish 25 days faster ($P < 0.001$), revise abstracts 6.0% less ($P < 0.001$) and are 11.6% less likely to have their authorship teams changed ($P < 0.001$) (See Table S8). Figure 4 shows these outcomes split out by regions. Authors from North America experience a wait time of 252 days from rejection to publication, revise abstracts by 37.9% and change authorship teams in 6.7% of cases, while authors from Africa experience a wait time of 293 days, revise by 48.0% and change authorship in 18.4% of cases (See Table S9).

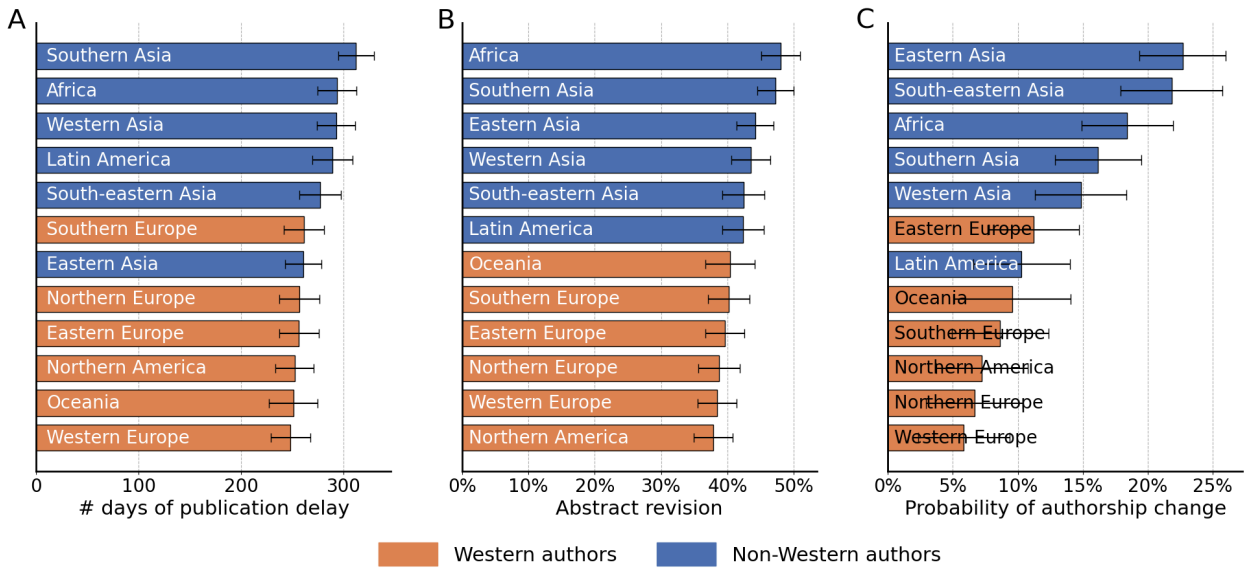


Fig. 4. *Coefficient estimates from regressions predicting regional disparities among published papers in (a) speed of publication, (b) abstract revisions, and (c) authorship team change. Western authors generally experience quicker post-rejection publication times and require fewer revisions and adjustments in authorship. The regression coefficients are displayed relative to the reference category: a submission to "Journal of Physics D: Applied Physics," desk-rejected in January 2018, with the corresponding author of unknown gender.*

One notable exception to the general Western-non-Western pattern is Eastern Asia, predominantly China, where authors have relatively low publication rate after rejection but, for the papers that get published, exhibit a much smaller journal prestige drop and shorter publication delay than most of Western authors.

We also examine citation as an additional publishing outcome. Using the usual regression specification and citation as the dependent variable, we find that within the first two years after publication, Western authors receive 0.33 fewer citations than non-Western authors ($P < 0.001$). However, drawing on recent work on "home bias" that argued that authors in some countries tend to cite work from their country disproportionately (30), we disaggregate citations into self- and external citations, and find that Western authors receive 0.11 fewer external citations ($P = 0.04$) (See Table S13 for regression results). This advantage for non-Western authors is relatively modest and comes at the cost of higher investment in time and effort before publication. They may need to dedicate significantly more resources to revisions and changes to authorship to achieve comparable or slightly better outcomes on these secondary metrics.

Overall, across a variety of dimensions, Western authors have quicker and smoother publication experiences post-rejection than non-Western authors of papers with similar publishing potential.

Resubmission shrinks the initial geographical gap in publishing

Tracking all research manuscripts submitted to the 62 IOP journals in our data between 2018-2022, we see in Figure 5A that there is a gap between Western authors and non-Western authors in acceptance (open circles) and that the gap shrinks after rejection and resubmission

(closed circles). Initially, 57.3% of Western and 33.6% of non-Western submissions to our journals were accepted, representing a publication gap of 23.7%. However, when we include submissions that were rejected and published elsewhere, 84.9% of the initial pool of submissions from Western authors and 72.1% from non-Western authors were ultimately published, representing a gap of only 12.8%. Taking post-rejection publication into account, nearly halves the initial publication gap as many non-Western authored papers are resubmitted.

Because rejected manuscripts can take a long time to be revised, resubmitted and finally published, we analyzed the subset of our data that had the longest time-window to be published elsewhere. Focusing on submissions in 2018, we tracked 32K manuscripts' publication status over four years. Figure 5B shows that results in this subset are similar to the full sample. All submissions accepted by the initial IOP journal (open circles) received decisions within about a year, after which the trendlines show no substantial changes: 58.3% of these 2018 submissions from Western countries and 33.8% from non-Western countries were accepted. Then rejected papers continue to be resubmitted and published elsewhere, and ultimately 85.0% of Western and 72.2% for non-Western submissions are published. Thus, accounting for publication after resubmission reduces the Western-non-Western publishing gap by 11.7%.

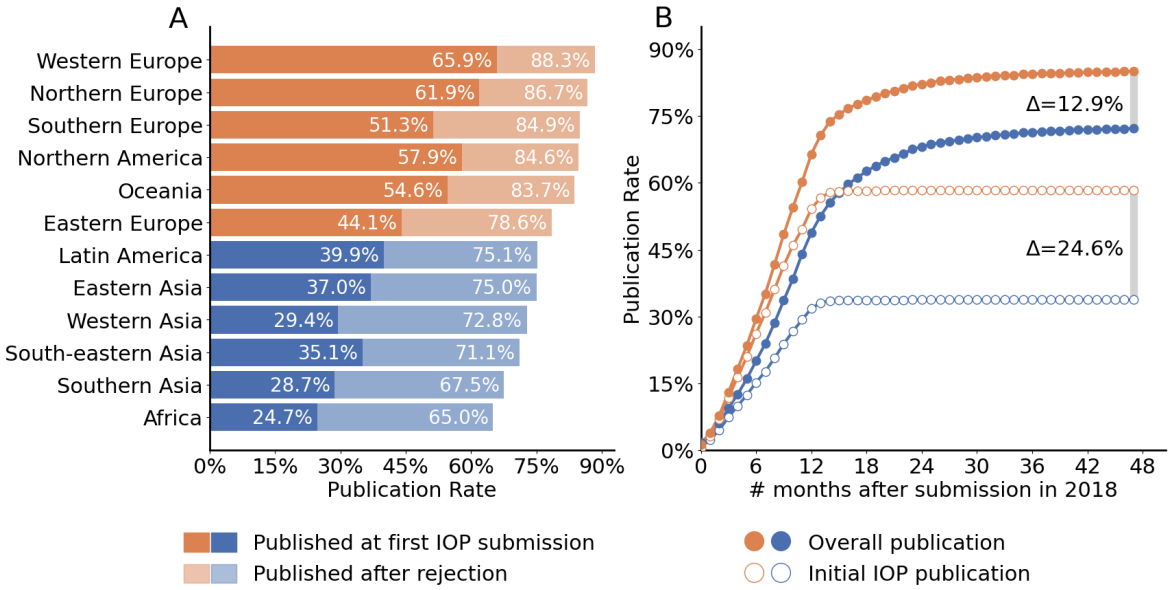


Fig. 5. *Raw data on the share of papers published by the initial IOP journal they were submitted to and those rejected-and-published-elsewhere.(a) The total length of the bar indicates the overall share of manuscripts submitted over five years that were eventually published, with darker bars showing acceptance rates of all submissions by initial IOP journals and lighter bars showing rejected-and-published-elsewhere acceptance rates of all submissions. Submissions from authors in the six Western regions have an 84.9% publication rate on average, while those from non-Western regions have a 72.1% publication rate on average. (b) Publication rate of submission from 2018 tracked over time. Submissions in 2018 from Western authors have a 24.6% higher first IOP acceptance rate than those from non-Western authors. After a presumably sufficient period for resubmitting and publishing rejected papers, Western authors have a smaller 12.9% higher overall publication rate.*

Procedural knowledge: Western co-authors and prior publishing experience

We hypothesized that the geographical gaps in post-rejection outcomes above were caused, in part, by different levels of procedural knowledge. If so, authors with more publication experience should have more procedural knowledge and better outcomes. Additionally, non-Western authors co-authoring with Western ones should be able to indirectly access procedural knowledge. We explore these arguments by measuring how the probability of being published varies across author experience level, measured by number of prior publications at the time of rejection, and by team composition.

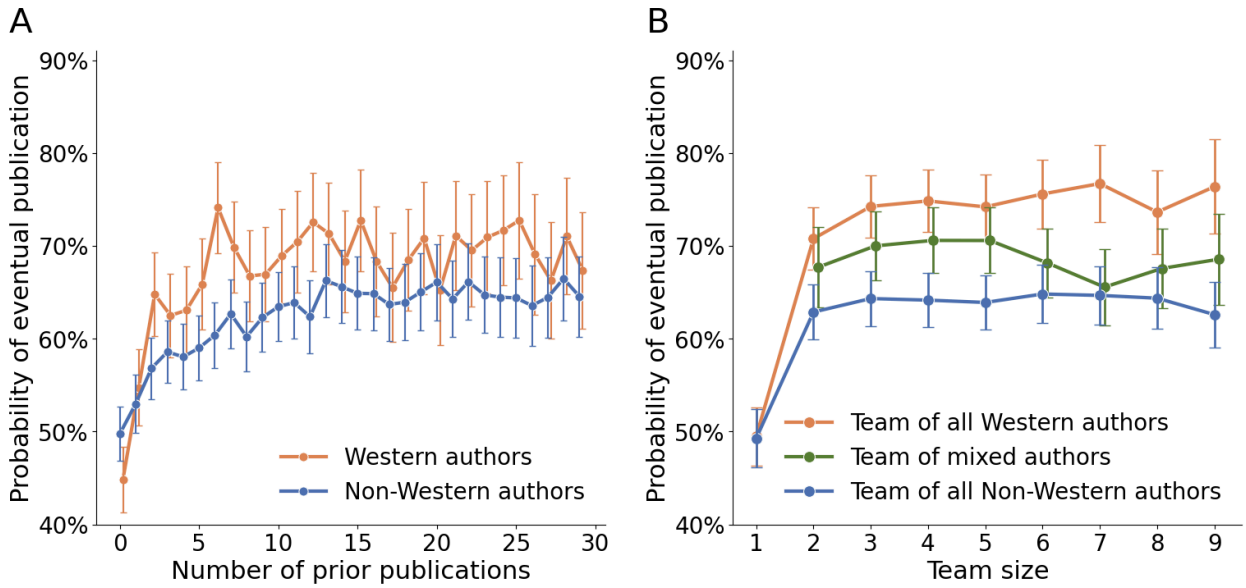


Fig. 6. *Estimates from regressions showing associations of prior publishing experience and team composition with the probability of rejected manuscripts being published. Panel A shows corresponding authors with more previous publications are positively related with higher chance of publication after rejection. Panel B shows having Western coauthors in the authorship team is related with higher chances of publication after rejection. See Supplementary Information S10 for regression specification and results.*

Figure 6 Panel A shows that authors with more experience are substantially more likely to ultimately publish rejected papers. For example, a manuscript with a non-Western corresponding author with no prior publication has a 13.7% lower probability of being published after rejection relative to a non-Western author with 10 publications by the time of rejection ($P < 0.001$) (See Table S14). The returns to experience appear to diminish at higher levels. Panel B shows that teams with all Western authors are most likely to publish rejected papers, followed by mixed teams and teams with all non-Western authors. Teams of all four Western authors are 10.7% more likely to publish than teams with all four non-Western authors ($P < 0.001$) (See Table S15). Overall, these results are consistent with the procedural knowledge hypothesis, which we probe more directly using a survey.

Procedural knowledge: survey

We use the survey responses, first, to collect arguably ground truth data on whether rejected submissions are published, as well as publication information which we later use as training data

for our logistic classifier. Of the 287 respondents, 188 reported that their rejected submissions were eventually published, resulting in a publication rate of 65.5%. The self-reports reveal a post-rejection publication gap between Western and non-Western authors, with 69.3% and 63.0% respectively, achieving publication. However, the estimate of the gap is imprecise and not statistically significant ($\chi^2(1, N=218) = 0.58$, $P = 0.44$; regression analysis (P=0.15)).

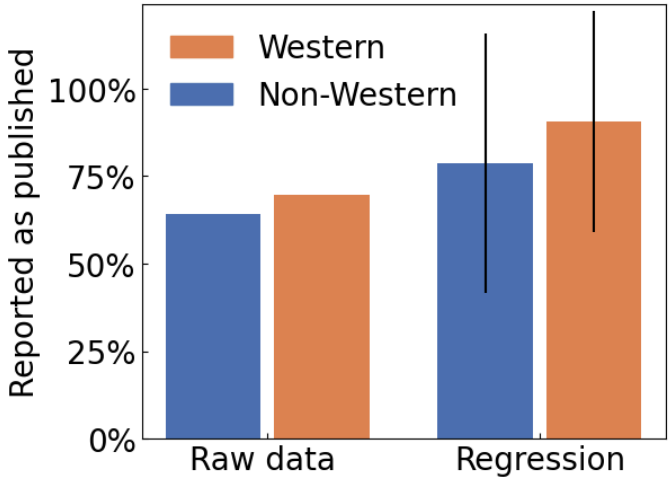


Fig. 7. *Disparities between Western and non-Western authors in reported publication rate of rejected manuscripts. Both survey responses and regression results indicate a higher likelihood of publication for authors from Western countries, which is not statistically significant..*

Second, we used the survey to probe for geographical differences in two aspects of procedural knowledge, interpretation of the rejection feedback and strategizing next steps, using two questions for each aspect. Figure 8 displays the regression coefficients of Western and non-Western authors in predicting answers to the four questions. The estimates show no significant difference between Western and non-Western authors in their perception of the negativity (Panel A) and fairness (Panel B) of their rejection decision letters. Similarly, we do not find geographical differences in intended or perceived revising effort (Panel C), and the prestige of the resubmission outlet (Panel D) (See Supplementary Information S11 for the full regression results) .

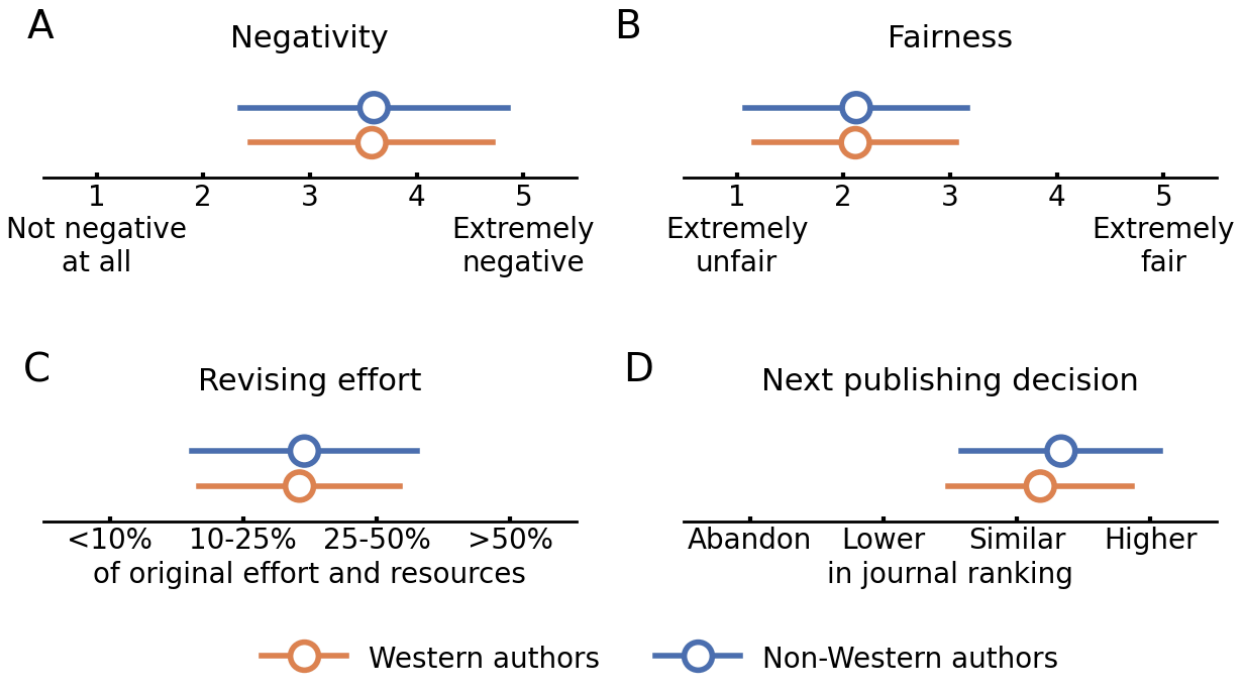


Fig. 8. *Estimates from regressions predicting four aspects of "procedural knowledge" — (a) negativity, (b) fairness of rejection feedback, (c) revision effort, and (d) next submission decisions — controlling for perceived quality and other covariates (See Table S17). Each circle represents the adjusted mean score for Western (orange) and Non-Western (blue) authors. None of the aspects differed across author geography at conventional levels of statistical significance.*

5. Discussion

Navigating scientific rejection can be a complex, multi-step process. In the context of publishing, rejection is rarely the end of the road for a paper, as authors can and do resubmit manuscripts elsewhere. Doing so successfully and efficiently requires procedural knowledge, such as how to interpret rejection feedback, and this knowledge is unlikely to be distributed evenly across people or space. We hypothesized that authors in Western countries, where many editors, reviewers, and other authors are based, have greater access to the procedural knowledge necessary for publishing in Western-based journals than authors in non-Western countries.

We explored this hypothesis using large-scale administrative data from the Institute of Physics Publishing, and tracked whether authors from different countries have different levels of post-rejection publishing success. Of course, not all rejections are equal, and our research design featured a key strength, which is to measure the perceived quality of rejected papers using the rejecting journal, peer review rounds and reviewers' recommendations in the last round of review. Controlling for perceived quality in this way enabled us to compare outcomes for papers with similar publishing potential. Additionally, a key concern is that the main dependent variable—whether a rejected paper is ultimately published—is geographically biased due to the indexing choices of the bibliometric databases used for identifying publications. Using a survey in which respondents self-reported the status of their rejected papers we do not find evidence supporting this concern.

Consistent with the procedural knowledge mechanism, we found that authors from Western countries have better post-rejection outcomes, on average. First, despite similar perceived quality at the time of rejection, Western authors were 5.9% more likely to publish the rejected papers elsewhere. Among those who ultimately publish, Western authors publish approximately 25 days faster and do 6% less abstract revising and 11.6% less authorship team change. While publishing faster and with less effort, as reflected by abstract and authorship team changes, is arguably desirable from a purely strategic perspective, it may come at a small cost in impact, as non-Western authors received 0.17 more external citations within the first two years of publication.

To assess whether these disparities can be linked to the procedural knowledge mechanism, we explored the associations between publication experience, team composition and post-rejection outcomes. We hypothesized that authors with more experience and teams with more Western authors have higher levels of procedural knowledge and have more success in navigating rejection. Consistent with the mechanism, we find teams with all Western authors are more likely to have their rejected manuscript published than teams with all non-Western authors and authors with a publication history are more likely to publish than those without prior experience in publishing.

We also tested the procedural knowledge hypothesis directly using a survey. The survey indicates that the disparities in post-rejection outcomes are unlikely to be caused by differential interpretation of rejection decisions or stated strategy for next steps. In particular, we do not find statistically significant differences between Western and non-Western authors in how fair or negative they thought rejection feedback was, or in the planned amount of revision and prestige of the target outlet for resubmission. While these results do not support the procedural knowledge hypothesis, the response rate and statistical power were low and the questions tested only some aspects of that knowledge, limiting strong conclusions. For example, there may be geographical differences in actual (vs. stated) revision and resubmission behavior, or appropriateness of the subsequent journals to which authors submit.

Nevertheless, despite controlling for plausible confounders, it is possible that our results have more to do with other, non-procedural-knowledge-related mechanisms. For example, tenure and promotion policies can vary by region, and affect how much time and effect authors can spend on the revision and resubmission process. Regional variations in the availability of funding and labor resources may also influence decision-making in the resubmission process. Lastly, journals to which authors submit after IOP may have pro-Western biases that are not already captured by IOP's peer reviewer recommendations, leading to those authors' better publishing outcomes.

This study has several limitations. First, although our data illuminate the publication trajectories of hundreds of thousands of submissions, these trajectories do not include the steps, if any, *before* submission to our set of 62 journals. It is possible, and in some cases even likely, that authors had previously submitted their work elsewhere and entered our dataset after rejection(s). This censoring of the trajectories may be particularly relevant if authors from some countries have more censoring of these earlier steps than others. For example, it is possible (even if unlikely) that authors from non-Western countries experienced more rejections prior to

submitting to our 62 journals, and after rejection at those, more quickly reach the number of rejections after which most authors abandon a project. Some support for the possibility that submission strategy varies geographically comes from the observation that in our dataset Western authors were more likely to get rejected from higher prestige journals. It is thus possible that controlling for the rejecting journal in our regression results did not fully account for all aspects of submissions strategy.

Second, our ability to test the procedural knowledge hypothesis was constrained by the multidimensional nature of this concept and the relatively low response rate and small sample size of the survey. Our survey results, which suggest that there are no substantial geographical differences in how authors interpret rejections and strategize about next steps, should be interpreted as suggestive and represent a fruitful area for more research.

Third, it is possible that despite similar reviewer recommendations, authors from different regions receive different messaging from editors in their decision letters. Although our survey provides some evidence against perceptions of the messaging varying across country groupings, it does not measure the messaging directly.

Lastly, we analyzed our data by categorizing many different scientific communities into countries, regions, and, at the crudent level, the Western and non-Western binary. These categories overlook significant variation. For example, analyzing post-rejection outcomes by country reveals heterogeneous patterns, which may be due to differences in procedural knowledge. For instance, Japan, though categorized as non-Western, has one of the highest publication rates. Meanwhile, Chinese authors frequently publish in relatively high-impact journals and experience minimal decreases in impact factor from submission to publication, with delays comparable to those in Northern Europe. These finer-grained results are consistent with certain non-Western countries or sub-communities possessing procedural knowledge levels similar to, or exceeding, some Western countries, leading to comparable or better publishing outcomes. We hope that our broad-strokes analysis stimulates future studies of heterogeneity.

6. Conclusion

Science progresses when the contributions of researchers are made public for other researchers to build upon. Yet making contributions public, primarily via publishing in peer reviewed journals, is rarely straightforward. Manuscripts are typically rejected, requiring revision and resubmission. Understanding of which researchers (and therefore which ideas) navigate the rejection and resubmission process successfully has been limited. This paper advanced that understanding by documenting several new empirical facts: authors from Western countries fare better after having their papers rejected than those from non-Western countries; they are on average more likely to publish the rejected papers, publish faster, revise less, and change authors less.

Taken together, these facts reveal a previously hidden cause of geographical disparities in visible knowledge – differential outcomes after rejection. This cause complements those established in prior work. Established causes have focused on inputs into papers stemming from differential access to resources and language skills (25, 26), biases of the peer reviewers (18, 27) and editors (50), and lastly biases of the audiences (29). We show that in between these steps, when

scientists revise and resubmit, papers by non-Western researchers are differentially likely to exit the publishing pipeline and end up in science's file drawer. Crucially, contributions ending up in the file drawer are not uniformly of lower quality than published ones; non-Western contributions are more likely to end up here even when they are of similar quality to Western ones.

This hidden cause that occurs during resubmission also helps to better contextualize the previously identified causes. First, it highlights that the biases of peer reviewers and editors of certain outlets that previous work has established are not as consequential as they would be in a world without resubmission. This is because rejected authors usually continue to resubmit. As they do so, the initial publication gap between Western and non-Western authors, which may be in part the result of evaluator biases, is partially mitigated over time. Second, the substantial geographical disparities observed in *post-publication* measures of impact like citations are *conservative*, because they generally do not account for the geographical disparity in papers that were written but never published.

Furthermore, differential access to the type of knowledge often available to insiders, such as how to interpret feedback, revise, and strategize about next steps, which we called "procedural knowledge" may contribute to the disparity in post-rejection outcomes. Previous work has provided suggestive evidence of the importance of procedural knowledge (34, 35). We add additional evidence: authors are more likely to publish after a rejection the more publishing experience they have, and teams of a certain size but with more Western co-authors are also more likely to publish after rejection. However, when we measured two aspects of procedural knowledge most directly – by asking authors through a small-scale survey how they interpret rejection feedback and strategize about next steps – we did not find geographical substantial differences. Overall, establishing the mechanisms behind post-rejection geographical differences more precisely continues to be a challenge, and an important area for future work.

If procedural knowledge is indeed an important mechanism driving publishing success as our work suggests, efforts could be made to democratize access to this knowledge. Editors and institutions might increase their efforts on international networking (51) and make more explicit the often opaque publishing norms, such as the opportunity to appeal rejections (52).

Acknowledgments

We are indebted to the Institute of Physics Publishing, particularly Kim Eggleton and Mikka Pers, for enabling this project. We thank Daniel Romero and members from Blablablab and DiscoveryLab at the University of Michigan for providing insightful feedback on this project. We also thank the participants of the following seminars and meetings for their valuable suggestions: Institute of Physics Publishing, University of Michigan Computational Social Science Working Group, University of Michigan Social Behavioral and Experimental Economics seminar, Annual Meeting of the Society for the Social Studies of Science, New York University Abu Dhabi Social Research and Public Policy, International Conference on the Science of Science and Innovation, and Strategy Science Doctoral Workshop.

M.T. thanks Schmidt Futures (Grant 2022-5-23-9) for generous financial support.

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Supplementary Information

S1. Data preprocessing

The dataset comprises manuscripts submitted to 62 peer-reviewed journals (listed in Table S1), spanning 36 distinct manuscript genres. However, certain manuscript types, such as invited submissions, inherently have no risk of rejection and thus will not be included in our analysis. We focused our analysis on 14 manuscript types with acceptance rates below 95%. Manuscripts with acceptance rates above 95% are more likely to be invited for submission and are typically not rejected. The types we used are listed in Table S2 below. Among these, "Paper" constitutes the majority at 83.1%.

The dataset also includes author information, including self-reported role in the team, country, institution name, and, if available, ORCID. For each author, only one self-reported institution and country is recorded.

We use the attributes of the author designated as the "corresponding author" to represent the team's characteristics. Out of 127k rejected submissions, 1.2k teams (0.99%) have multiple corresponding authors. In these cases, we use the last author listed in the corresponding author list as the primary corresponding author. It is noteworthy that most teams are from institutions within a single region. Among the 119k teams with multiple authors, 81.2% have all authors from institutions in the same region.

Journal name (Column 1)	Journal name (Column 2)
2D Materials	Journal of Physics: Photonics
Biofabrication	Journal of Radiological Protection
Bioinspiration & Biomimetics	Machine Learning: Science and Technology
Biomedical Materials	Materials Research Express
Biomedical Physics & Engineering Express	Materials for Quantum Technology
Classical and Quantum Gravity	Measurement Science and Technology
Electronic Structure	Methods and Applications in Fluorescence
Engineering Research Express	Modelling and Simulation in Materials Science a...
Environmental Research Communications	Multifunctional Materials
Environmental Research Letters	Nano Express
Environmental Research: Climate	Nano Futures
Environmental Research: Ecology	Nanotechnology
Environmental Research: Health	Neuromorphic Computing and Engineering
Environmental Research: Infrastructure and Sust...	New Journal of Physics
European Journal of Physics	Nonlinearity
Flexible and Printed Electronics	Physica Scripta
IOP SciNotes	Physical Biology
Inverse Problems	Physics Education
Journal of Breath Research	Physics in Medicine & Biology
Journal of Micromechanics and Microengineering	Physiological Measurement
Journal of Neural Engineering	Plasma Physics and Controlled Fusion
Journal of Optics	Plasma Research Express
Journal of Physics A: Mathematical and Theoretical	Plasma Sources Science and Technology
Journal of Physics B: Atomic, Molecular and Opt...	Progress in Biomedical Engineering
Journal of Physics Communications	Progress in Energy
Journal of Physics D: Applied Physics	Quantum Science and Technology
Journal of Physics G: Nuclear and Particle Physics	Reports on Progress in Physics
Journal of Physics: Complexity	Semiconductor Science and Technology
Journal of Physics: Condensed Matter	Smart Materials and Structures
Journal of Physics: Energy	Superconductor Science and Technology
Journal of Physics: Materials	Surface Topography: Metrology and Properties

Table S1. *List of 62 Institute of Physics journal names.*

Manuscript Type	No. of submissions
Paper	188527
Letter	11527
Special Issue Article	11371
Topical Review	5651
Note	1559
Perspective	647
Technical Note	629
Review Article	449
Article	393
Report on Progress	168
Tutorial	155
Fast Track Communication	135
Topical Issue Article	84
Key Issues Review	61

Table S2. *List of manuscript types and their corresponding number of submissions..*

S2. Matching rejected manuscripts with OpenAlex database

Previous research on the fate of rejected manuscripts has primarily relied on querying bibliometric databases using the titles of rejected manuscripts or keywords from these titles. However, this approach is limited, as search effectiveness is highly sensitive to query terms; only results that closely match the exact query tend to be retrieved. Titles and abstracts, however, can undergo significant changes during the revision and resubmission process, which makes it challenging to identify the effective query.

In this study, we performed searching under the assumption that the authorship team remains mostly intact. Even though a rejected manuscript is eventually published with major alteration, we assume at least one original author would be part of the team, which allows us to track the publication.

Based on this assumption, we employ a three-step process to search rejected manuscripts with records in the OpenAlex database, as illustrated in Figure S1: (1) find all potential author records in OpenAlex based on the authors in the rejected manuscript's team, (2) extract these author candidates' publications dated after the rejection, and (3) identify the "rejected-and-published" papers based on similarities in their author names, titles, and abstracts.

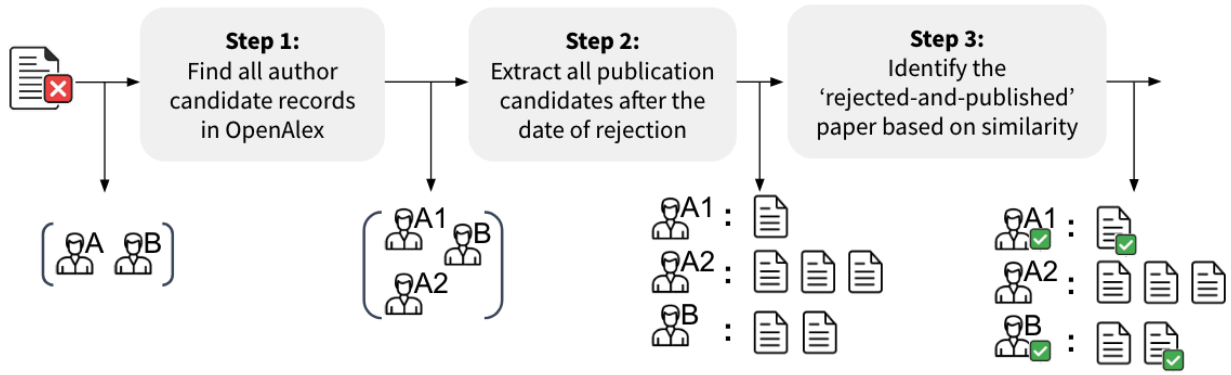


Figure S1. *Author and paper records searching process in three steps.*

Step 1. We start with linking authors with potential records in OpenAlex using available information.

In the administrative data provided, authors self-reported their information when submitting their manuscripts, including their first and last name, institution, country, gender, and, if available, ORCID. ORCID is a unique and reliable identifier for matching author entities in bibliometric datasets and is also our ideal query for locating author records in OpenAlex. However, not all authors have this identifier available—specifically, only 19.1% of all authors and 26% of corresponding authors have provided their ORCID.

Since our goal is not to link each author to a single, correct record in OpenAlex but rather to find all potential author records that might include the rejected-and-published papers in their

publication, we also implemented two supplementary name-based methods in addition to ORCID-based matching.

The first name-based supplementary method uses the authors' full names as the query. The second name-based method searches using the author's last name, country, and field of study. This second method complements the first by capturing cases that might be missed due to potential variations in how full names are presented, such as abbreviated first names (e.g. *Alexander Smith* listed as *A. Smith*), inconsistent transliterations of names from non-English languages (e.g. *Louisa Schmidt* listed as *Loisa Schmidt*), or inconsistent use of hyphens in multi-part first names (e.g. *Lin Ying Choi* listed as *Lin-Ying Choi*). (All names provided here are fictional and used as examples.)

To keep the list of potential author records to a manageable length, it operates by searching by authors' last name and filter the returned records by three criteria:
1) among all alternative names of the matched record in OpenAlex, there must be an alternative full name with at least 80% text similarity to the author's full name.
2) the country of the matched record must align with the self-reported country of the author.
3) the matched record must belong to the field "Physics." Fields are classified by OpenAlex using titles and abstracts. The classifications are validated using Wikipedia, with the details provided here: https://github.com/ourresearch/openalex-concept-tagging.

In this way, we retrieve a list of potential author records for each author. We further validated the recall of the name-matching method by using ORCID-matched records as ground truth. Here, recall is defined as whether each returned author list contains the correct record at least once. Specifically, among authors with available ORCID information, searching for these authors using the name-matching method returned a list of records that included the 'true' ORCID-matched record 83.0% of the time.

We further validated the recall of the name-matching method by using ORCID-matched records as ground truth. Here recall is also defined as the hit rate, which indicates whether each returned author list contains the correct record at least once. Specifically, among authors with available ORCID information, searching for these authors using the name-matching method returned a list of records that included the 'true' ORCID-matched record 83.0% of the time.

Overall, as shown in Table S3, among 586k authors, we were able to match 112k (19.1%) of authors with 100% recall using ORCID-based matching. The remaining 445k (76.0%) were matched via name-based methods with approximately 83.0% recall, resulting in 369k correct matches. This resulted in an overall recall rate of 82.1% (481k out of 586k).

Author matching	ORCID-based match	ORCID not available or no match	
Name-based match	105,989 (87,921 common matches)	**444,992** (76.0%)	473,806
Name-based no match	6,222	28,814	35,036
	112,211(19.1%)	473,806	586,017

Table S3. *Number of all authors matched via ORCID-based or name-based methods.*

Step 2. We then extract the publication lists for all author candidates within the manuscript team since the date of rejection. These lists of publication candidates are retained for further classification.

This method of retrieving publication lists increases recall by extracting all recent publications from all possible author matches. This method is robust against potential mis-index issues, incorrect matching in the dataset, or limitation in the searching capabilities of OpenAlex's query function. As long as the manuscript is published and indexed in the dataset OpenAlex, we can reliably locate it if we have at least one author's correct ID.

For each author, the median number of author candidate records is 3, and the median number of publication candidates is 15. The recall for this step is the probability of including the rejected paper in the publication list, if it has been published and indexed in OpenAlex. As our author matching recall is 82.1%, which means for solo-authored papers, there is 82.1% likelihood to include it in the publication list for further matches. As team size increases, recall improves because the presence of more authors increases the likelihood that at least one will contribute to a correct classification.: 96.8% for two-author teams, 99.4% for three-author teams, and over 99.9% for teams with more than three authors.

In terms of the distribution of team sizes within our dataset, 10.5% of teams are solo authors, 16.3% consist of two authors, 17.5% have three authors, and 55.7% have teams larger than three. Given this distribution, the overall likelihood of a manuscript being correctly included in our list of paper candidates is estimated to be 97.5%.

Step 3 is explained in Supplementary Information S3.

S3. Logistic regression classifier to identify the "rejected-and-published" paper

After extracting a list of publication candidates for each rejected manuscript, in Step 3, we train a logistic regression classifier to identify the true "reject-and-published" version from this list.

The classifier is trained using a curated dataset with both positive and negative examples. For ground truth data, we collect responses through a survey, where we directly ask respondents to provide the URLs of their publications that corresponded to their rejected submissions (See S10 for survey instruments). Out of 278 respondents, 106 provided the publication information, and these "reject-and-published" versions were labeled as positive samples.

To construct the negative samples, we used the same method as in Step 2 where we generated the list of publication candidates. We searched for papers published by all potential authors from the 106 authorship teams after the time of rejection and compiled a set of 10,270 potential publications (excluding the true publication). These served as negative samples for the classifier.

It is also worth noting that because projects may change substantially over time, deciding whether an earlier version is "the same" project as a later one is ambiguous: at some level of change, the earlier version may be considered abandoned and the later one a new project. Therefore, instead of arbitrarily setting a threshold based on abstract similarity or other features,

we trained a model based on pairs that authors self-identify as the same project after rejection. Note that survey respondents were not instructed on how to decide whether an ultimately published paper is from the same project as the rejected one.

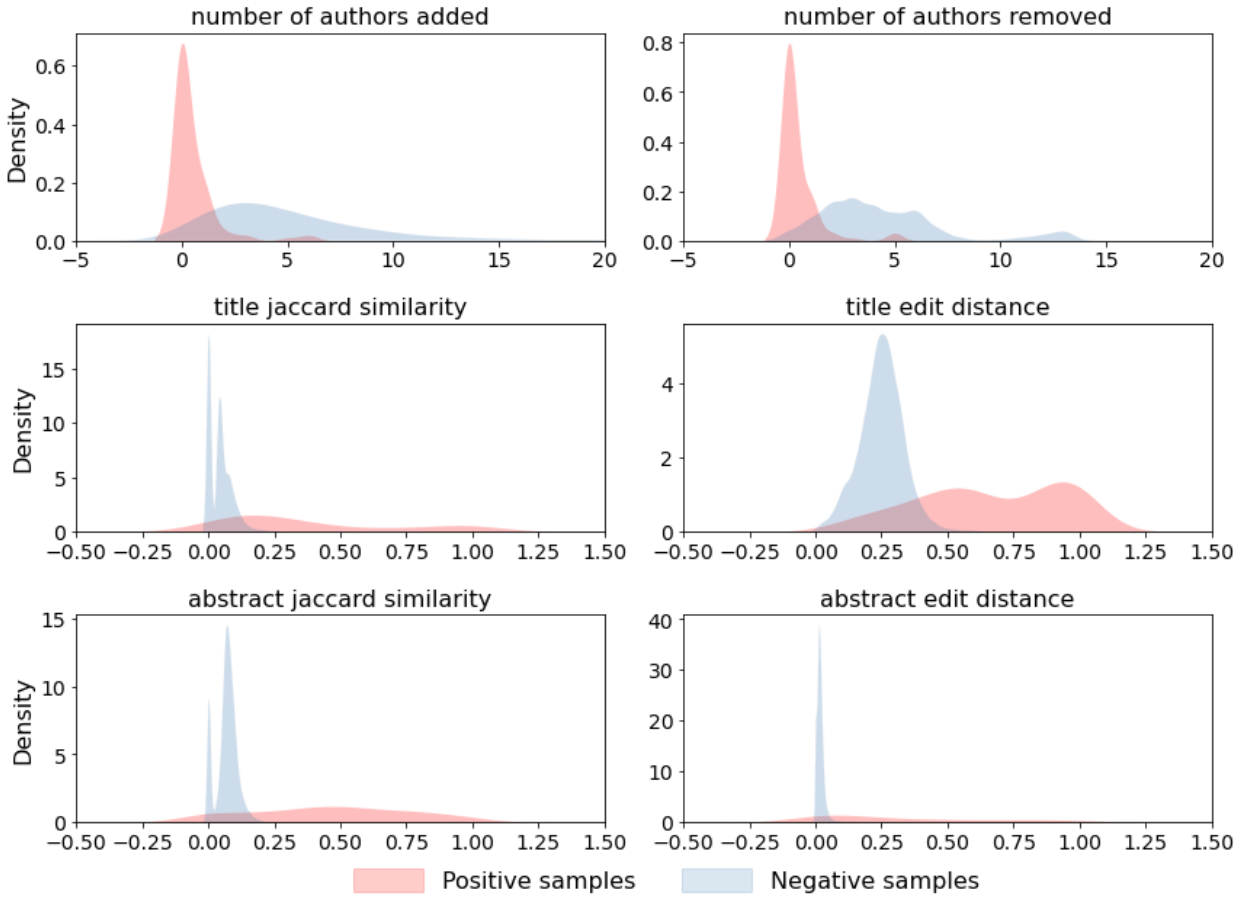


Figure S2. *Distributions of features of positive (rejected-published match) and negative samples for training the logistic classifier.*

The features are constructed as the similarity between each positive/negative sample and its corresponding rejected submission. We use author, title, and abstract similarity to create six features to train the classifier.

For author similarity, we use two features to indicate team change: number of original authors left and number of new authors added. Author comparison is measured by name similarity. If the name similarity between two authors exceeds 0.95, we classify them as the same author. Title and abstract revisions are quantified using two aspects of text similarity: text edit distances (measured by minimal changes in word) and word usage share (measured by overlapping in the set of words used via jaccard index), each capturing how closely the sequences and word choices align. The feature distributions for positive and negative samples are shown in Figure S2. Positive samples (the reject-and-published versions) exhibit much higher title and abstract similarity and fewer changes in authorship.

The train and test datasets were split in a 0.7:0.3 ratio, resulting in 7,263 samples for training (7,189 negative and 74 positive) and 3,113 samples for testing (3,081 negative and 32 positive). The classifier achieved its best F1 performance at 0.857 with a precision of 0.97 (meaning 25 out of 26 positive predictions were correct) and a recall of 0.78 (meaning 25 out of 32 actual positive cases were correctly identified). It suggests this classifier is reliable in identifying the true publication but may still miss some true published versions. Also it is worth noting that there are minimal precision differences between papers of Western and non-Western authors (0.97 for Western vs 0.98 for non-Western) and slightly higher recall of non-Western authors (0.72 for Western vs 0.79 for non-Western). The higher recall for non-Western authors indicates the classifier is better at finding the publication of non-Western authors and misses more published versions of Western authors. And our main results still show that more publications from Western authors are identified and non-western authors still have a lower rate of finding a published version. It suggests our results are potentially conservative.

Since the threshold for classifying a manuscript as 'published' is subjective and yields high precision but low recall, we also tested the classifier with an alternative threshold that produces a much higher recall of 0.865 and a lower precision of 0.78, resulting in a comparable F1 score of 0.833. This adjustment led to more rejected manuscripts being classified as 'published,' yet our main findings on geographical disparities remain consistent and significant. See Table S13 for regression results on the publishing outcomes.

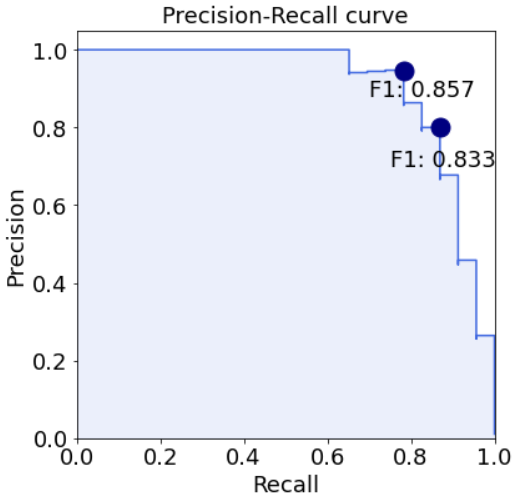


Figure S3. *Recall and precision curve for different thresholds of logistic regression.*

We then construct our major outcome of interest "*If.Published*" based on the classification of this logistic regression. If a match is found within the publication candidate list, the rejected submission is considered ultimately published; if no match is found, it is not published yet. For lists with multiple matches, we identify the publication with the highest probability as the published version, from which we then obtain metadata to compare publishing outcomes.

S4. Submission and publication statistics of papers from Western and non-Western countries

The 12 major groups include Northern America, Northern Europe, Western Europe, Southern Europe, Eastern Europe, Oceania from Western regions, and Latin America and the Caribbean, Western Asia, Africa, Southern Asia, Eastern Asia and South-eastern Asia from non-Western regions. Here Oceania specifically refers to Australia and New Zealand.

Country	# Submission	First IOP submission (%)	Post-rejection (%)	Region
China	70357	30.5	33.7	Eastern Asia
India	28424	23.7	49.4	Southern Asia
USA	18064	55.8	28.8	Northern America
Iran	9593	17.8	57.4	Southern Asia
Germany	6755	65.8	22.6	Western Europe
United Kingdom	6422	62.1	23.6	Northern Europe
Japan	5209	51.1	34.2	Eastern Asia
Pakistan	5055	18.1	38.8	Southern Asia
Korea	4691	37.3	38.9	Eastern Asia
Russian Federation	4306	39.1	38.1	Eastern Europe
Turkey	4176	22.6	56.6	Western Asia
France	3656	59.0	28.8	Western Europe
Italy	3648	52.4	34.9	Southern Europe
Brazil	3596	32.3	38.9	Latin America
Egypt	2937	15.9	51.6	Africa
Canada	2826	50.0	34.9	Northern America
Spain	2592	47.7	35.9	Southern Europe
Australia	2485	52.3	31.2	Oceania
Taiwan	2048	31.1	39.9	Eastern Asia
Mexico	2004	36.6	38.1	Latin America
Saudi Arabia	1817	21.4	46.7	Western Asia
Poland	1772	38.6	45.2	Eastern Europe
Netherlands	1459	64.8	24.0	Western Europe
Malaysia	1439	19.6	42.8	South-eastern Asia
Sweden	1197	60.1	30.3	Northern Europe
Algeria	1187	16.4	46.1	Africa
Switzerland	1137	69.5	20.2	Western Europe
Iraq	1087	12.2	52.9	Western Asia
Czech Republic	906	48.9	31.6	Eastern Europe
Belgium	888	56.3	26.3	Western Europe

Table S4. *Descriptive statistics of the number of submissions and publication rate of both stages (first IOP submission and post rejection) of each country and its corresponding region. Top 30 countries with the most submissions are shown in this table.*

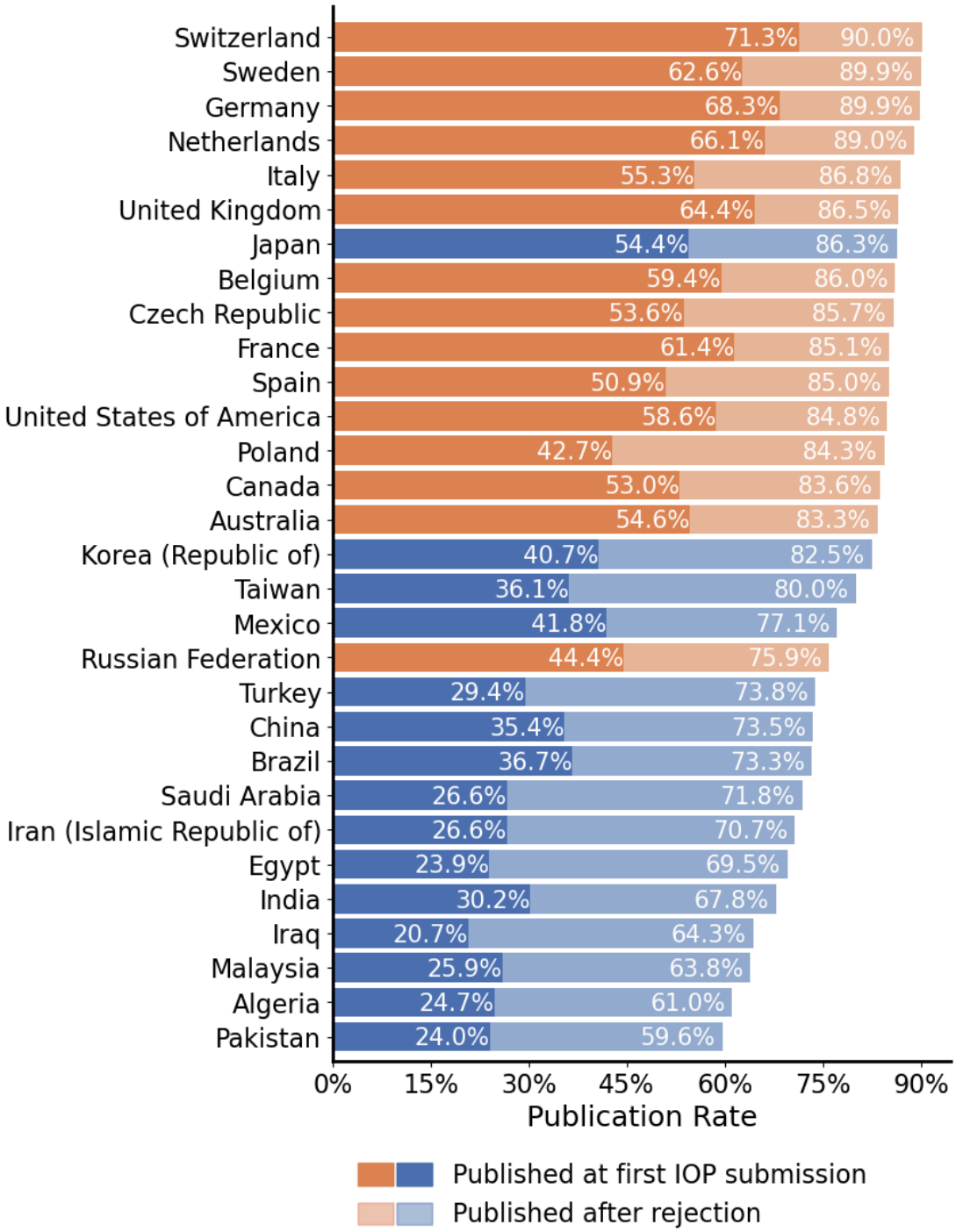


Figure S4. *Publication rate at initial and post-rejection stages of 30 countries with most submissions. Higher acceptance rate of first IOP submission and higher publishing rate of post-rejection phase of Western countries shown via raw data.*

We observed that 51% of Western and 35% of non-Western submissions were accepted after their first IOP submission. Among the rejected manuscripts, 58% of those from Western authors and 32% from non-Western authors were ultimately published.

S5. Review recommendation positivity and "Perceived Quality"

We utilize the peer review recommendations a manuscript received in the last round before rejection to proxy the 'expert-evaluated quality.' The distribution of peer review rounds of Western and non-Western authors are shown below. Approximately two-thirds of the rejected submissions are desk rejected, and one-third of them went through one round of review. Only 2.48% are rejected after two or more rounds of review.

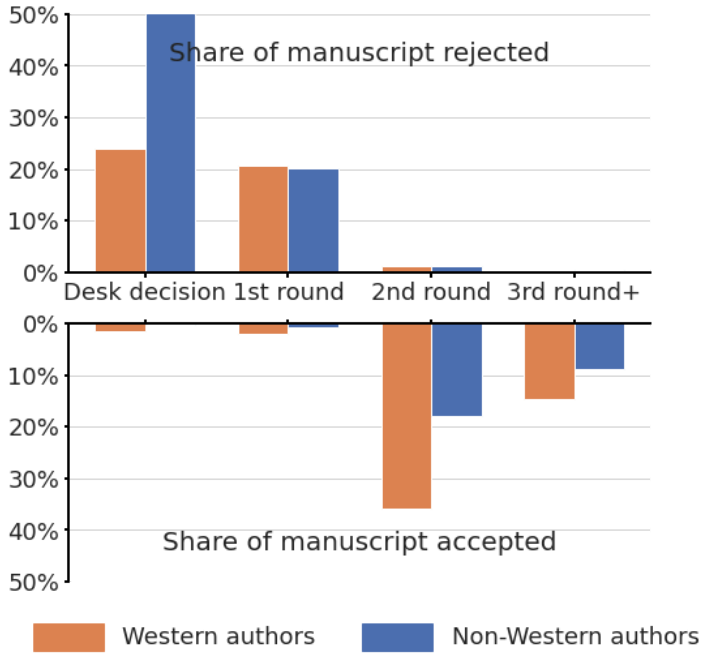


Figure S5. *Share of rejection and acceptance in different peer review rounds of manuscripts from Western and non-Western authors.*

Here we classify the reviewer's recommendation into four major levels of positivity, according to the publication potential each recommendation indicates. Here Level 1 of positivity includes recommendations such as "*Reject*" and "*Manuscript is fundamentally flawed*"; Level 2 of positivity includes recommendations such as "*Reject but may be resubmitted for consideration after expansion and/or revision*" and "*Reject but may resubmit following substantial revisions*"; Level 3 of positivity includes recommendations such as "*Major revision required before acceptance*", "*Major revision and resubmission recommended*", "*Revisions are required*"; Level 4 of positivity includes recommendations such as "*Accept*" and "*Manuscript displays scientific rigor - further revisions are optional*". The share of peer review rounds and review recommendation set are shown as below:

Number of rounds of review	Percentage(%)
0 / Desk Rejection	65.56
1	31.96
2	1.99
3	0.40
4	0.08
5	0.01
Review round + Review recommendations	**Percentage(%)**
1_{st} round, 1	28.20
1_{st} round, 1, 3	15.14
1_{st} round, 1, 1	13.94
1_{st} round, 1, 1, 3	12.32
1_{st} round, 1, 3, 3	3.28
1_{st} round, 3	2.65
1_{st} round, 3, 3	2.64
1_{st} round, 1, 1, 4	2.22
1_{st} round, 1, 4	1.43
1_{st} round, 1, 1, 3, 3	1.32
2_{nd} round, 3, 3	1.32
2_{nd} round, 3, 3, 4	1.20
1_{st} round, 1, 3, 4	1.12
1_{st} round, 2	0.98
2_{nd} round, 3	0.82

Table S5. *Distribution of peer review rounds and 15 most common review recommendation outcomes. The outcome is displayed as a combination of the number of peer review rounds and the set of review recommendations in the last round.*

S6. Testing bias in editor decisions

We examine post-rejection differences while conditioning on peer reviewer recommendations from the rejecting journals. This design assumes that reviewer recommendations (and consequently *Perceived Quality*) are some combination of quality and potential pro-Western bias from either reviewers and/or editors. One possibility of bias that may confound our results is if editors hold Western and non-Western authors to different standards, resulting in their differential chances of being rejected. We examined whether editors exhibit bias in their decisions—Accept, Revise, Reject—when presented with the same set of reviewer recommendations for submissions from Western and non-Western authors.

Because of the difficulty of achieving convergence with a logistic regression model that includes many dummy variables, we employed an OLS model, using a separate dependent variable for each pair of possible outcomes. The regression design is presented as follows:

$$Editor.Decision_i = \beta_0 + \beta_1 If.Western_i + \beta_2 Anonymization_i + \sum_j \beta_{3,j} Perceived.Quality_j + \beta_4 Author.Gender_i + \beta_5 Team.Size_i + \sum_k \beta_{6,k} Month_k + \epsilon$$

	Dependent variable: Editorial decision for next round	
	$\text{Reject}_{(0)}$ vs. $\text{Revise+Accept}_{(1)}$	$\text{Reject+Revise}_{(0)}$ vs. $\text{Accept}_{(1)}$
Intercept	0.884***	0.057
	(0.149)	(0.138)
Western author	**0.021*** **	**0.001**
	(0.001)	**(0.001)**
Anonymization	0.002	-0.005*
	(0.002)	(0.002)
Team size	0.001***	0.000
	(0.000)	(0.000)
Gender: Male	0.016***	-0.001
	(0.001)	(0.001)
Gender: Female	0.014***	-0.001
	(0.002)	(0.002)
Perceived Quality Fixed Effect	Yes	Yes
Month of Rejection	Yes	Yes
Observations	197370	197370
R^2	0.727	0.814
Adjusted R^2	0.720	0.809
Note:		*p<0.05; **p<0.01; ***p<0.001

Table S6. *Results of OLS regressions predicting editor decisions conditional on perceived quality, month of rejection, and author covariates.*

The dependent variable, "*Editor.Decision*," is a binary variable indicating whether the manuscript outcome for each peer review round is (1) reject versus revise/accept, or (2) reject/revise versus accept. The variable "*Anonymization*" indicates whether the author opted to anonymize their submission. "*Perceived.Quality*" is constructed similarly to the main regression specification but includes recommendation feedback not only in the final round before rejection but also from each peer review round. The regression shows that conditional on reviewer recommendations, Western authors are slightly more likely than non-Western to get a Revise/Accept instead of Reject (2.1%). These results are suggestive of small pro-Western bias in editors' decisions. As we discuss below, such bias should make our results conservative.

Specifically, if editors have a pro-Western bias, then given two papers with the same *Perceived Quality*, one by a Western author and another by a non-Western one, the paper by the Western author should be accepted more often. Accepting the strong and marginal Western papers from the pool of *submissions* leaves in the pool of *rejected* papers only weak Western papers, but weak *and* marginal non-Western papers. In other words, non-Western *rejected* papers should be stronger on average.

If the bias is idiosyncratic to the rejecting journal and subsequent journals are unbiased, then the Western papers should have weaker post-rejection outcomes. If the bias is similar at other journals, the Western paper should have similar ultimate outcomes to the similarly perceived non-Western one.

For potential reviewer bias, if reviewers have a similar pro-Western bias, then given two papers with the same *Perceived Quality*, one by a Western author and another by a non-Western one, the paper by the Western author should be weaker. Consequently, if the bias is idiosyncratic to the rejecting journal and subsequent journals are unbiased, then the Western paper should have weaker ultimate outcomes. If the bias is similar at other journals, the Western paper should have similar ultimate outcomes to the similarly perceived non-Western one.

In summary, potential biases in reviewer and editor decisions should push Western papers towards worse post-rejection outcomes, but empirically we find the opposite. So as long as the biases are pro-Western, our research design yields conservative estimates of the gap in post-rejection outcomes.

S7. Model specification and regression analysis of publishing outcome

We control for author level characteristics for confounding variables. Our analysis relies mainly on the characteristics of corresponding authors, as these individuals are usually the senior investigator and are primarily responsible for submission and resubmission decisions. Over 97% of corresponding authors self-reported their country, gender, affiliation and experience level in our administrative data, so we maintain high confidence of the accuracy.

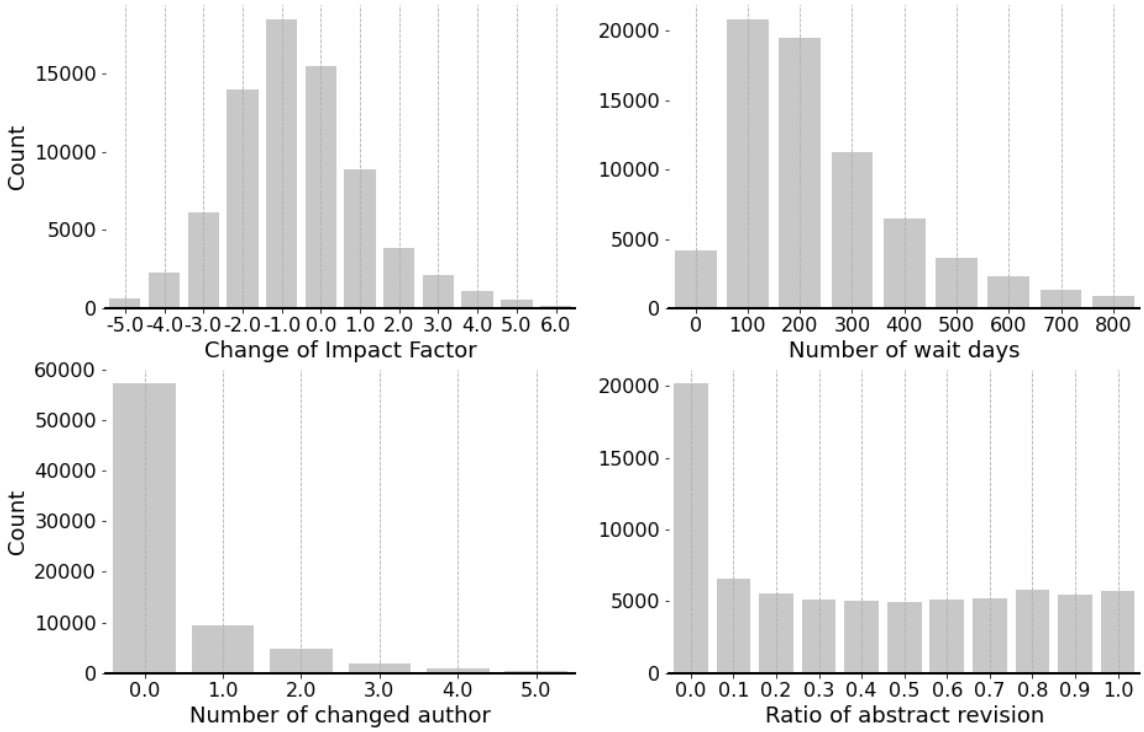


Figure S6. *Distribution of outcome variables: change of impact factor, number of wait days, number of changed authors and ration of abstract revision. On average for rejected manuscripts that eventually get published, they tend to experience a decline in journal prestige of -0.66 impact factor as authors resubmit to lower tier journals with higher chance of publication. Authors take an additional eight months to resubmit and achieve publication with approximately 0.44 authors joining or leaving the team, and revise the abstract 40.0% less.*

	count	mean	std	min	25%	50%	75%	max
If.Western	125990	0.21	0.41	0	0	0	0	1
Author.Gender	125990	0.75	0.37	0.0	0.5	1.0	1.0	1.0
Author.Seniority	125990	47.14	159.90	0	4	20	56	12763
Team.Size	125991	4.18	2.63	1	2	4	5	99
Month	126248	29.99	17.20	0	15	30	45	68.00
Team.Composition	125990	0.23	0.39	0.0	0.0	0.0	0.5	1.0

Table S7. *Descriptive statistics of author and team covariates.*

We use OLS model with the following specifications:

$$Publishing.Outcome_i = \beta_0 + \beta_1 If.Western_i + \beta_2 Author.Seniority_i + \beta_3 Author.Gender_i + \beta_4 Team.Size_i + \sum_k \beta_{5,k} Month_k + \sum_l \beta_{6,l} Perceived.Quality_l + \epsilon$$

The regression results are shown as below:

	Published or not	Wait days	Abstract revision	Prob. of author change
Intercept	0.600***	285.375***	0.454***	0.191***
	(0.015)	(8.933)	(0.014)	(0.017)
Western author	0.059***	-24.515***	-0.060***	-0.116***
	(0.004)	(2.097)	(0.003)	(0.004)
Team size	0.008***	-4.660***	-0.010***	0.019***
	(0.001)	(0.344)	(0.001)	(0.001)
Author prior publications	0.000***	-0.013*	-0.000**	0.000
	(0.000)	(0.006)	(0.000)	(0.000)
Gender: Female	0.057***	-2.361	0.014**	-0.015*
	(0.005)	(3.220)	(0.005)	(0.006)
Gender: Male	0.078***	-12.740***	-0.006	-0.004
	(0.004)	(2.544)	(0.004)	(0.005)
Perceived Quality Fixed Effect	Yes	Yes	Yes	Yes
Month of Rejection	Yes	Yes	Yes	Yes
Observations	125972	74757	74757	74757
R^2	0.066	0.072	0.054	0.066
Adjusted R^2	0.050	0.050	0.031	0.044
Note:				*p<0.05; **p<0.01; ***p<0.001

Table S8. *Regression estimates from OLS models predicting publishing outcomes. The reference category is defined as follows: a submission to Journal of Physics D: Applied Physics, desk-rejected in January 2018, with the corresponding author of unknown gender.*

We also replace the variable "*If.Western*" to "*Author.Region*" and omit the intercept, which allows us to calculate the coefficients for all 12 regions. The model is specified as follows:

$$Publishing.Outcome_i = \sum_j \beta_{1,j} Author.Region_j + \beta_2 Author.Seniority_i + \beta_3 Author.Gender_i + \beta_4 Team.Size_i + \sum_k \beta_{5,k} Month_k + \sum_l \beta_{6,l} Perceived.Quality_l + \epsilon$$

The regression results are shown as below:

	Published or not	Wait days	Abstract revision	Prob. of author change
Northern America	0.656***	252.001***	0.378***	0.072***
	(0.016)	(9.450)	(0.015)	(0.018)
Northern Europe	0.675***	256.862***	0.387***	0.067***
	(0.017)	(10.084)	(0.016)	(0.019)
Southern Europe	0.707***	261.015***	0.402***	0.086***
	(0.017)	(9.956)	(0.016)	(0.019)
Western Europe	0.668***	247.955***	0.384***	0.058**
	(0.017)	(9.833)	(0.015)	(0.018)
Eastern Europe	0.627***	256.326***	0.396***	0.112***
	(0.016)	(9.764)	(0.015)	(0.018)
Oceania	0.656***	250.725***	0.404***	0.096***
	(0.021)	(12.080)	(0.019)	(0.023)
Latin America	0.621***	288.949***	0.424***	0.103***
	(0.017)	(9.985)	(0.016)	(0.019)
Africa	0.596***	293.694***	0.480***	0.184***
	(0.016)	(9.708)	(0.015)	(0.018)
Eastern Asia	0.600***	260.415***	0.442***	0.227***
	(0.015)	(8.982)	(0.014)	(0.017)
South-eastern Asia	0.604***	277.122***	0.424***	0.218***
	(0.017)	(10.405)	(0.016)	(0.020)
Southern Asia	0.590***	312.042***	0.472***	0.162***
	(0.015)	(9.005)	(0.014)	(0.017)
Western Asia	0.668***	292.558***	0.435***	0.149***
	(0.016)	(9.535)	(0.015)	(0.018)
Team Size	0.008***	-2.791***	-0.009***	0.017***
	(0.001)	(0.354)	(0.001)	(0.001)
Author prior publications	0.000***	-0.007	-0.000**	-0.000
	(0.000)	(0.006)	(0.000)	(0.000)
Gender: Male	0.077***	-15.405***	-0.008*	-0.001
	(0.004)	(2.539)	(0.004)	(0.005)
Gender: Female	0.056***	-5.090	0.012*	-0.013*
	(0.005)	(3.213)	(0.005)	(0.006)
Perceived Quality Fixed Effect	Yes	Yes	Yes	Yes
Month of Rejection	Yes	Yes	Yes	Yes
Observations	125972	74757	74757	74757
R^2	0.067	0.078	0.055	0.071
Adjusted R^2	0.052	0.056	0.033	0.049
Note:				*p<0.05; **p<0.01; ***p<0.001

Table S9. *Coefficient estimates from regressions predicting publication outcome by different regions after controlling for "Perceived Quality" and other key covariates, The reference category is defined as follows: a submission to Journal of Physics D: Applied Physics, desk-rejected in January 2018, with the corresponding author of unknown gender.*

We also show that controlling for expert-perceived quality, using "*Rejection.Code*", is effective. The regression results without control are shown below and the effect size is reduced but remains substantial.

	Published or not	Published or not	Wait days	Wait days	Abs. revision	Abs. revision	Author change	Author change
Intercept	0.600***	0.488***	285.375***	315.423***	0.454***	0.490***	0.191***	0.204***
	(0.015)	(0.014)	(8.933)	(8.486)	(0.014)	(0.013)	(0.017)	(0.016)
Western author	0.059***	0.071***	-24.515***	-14.088***	-0.060***	-0.056***	-0.116***	-0.139***
	(0.004)	(0.003)	(2.097)	(1.969)	(0.003)	(0.003)	(0.004)	(0.004)
Team size	0.008***	0.016***	-4.660***	-6.808***	-0.010***	-0.013***	0.019***	0.019***
	(0.001)	(0.001)	(0.344)	(0.315)	(0.001)	(0.000)	(0.001)	(0.001)
Author prior pubs.	0.000***	0.000***	-0.013*	-0.018**	-0.000**	-0.000***	0.000	0.000
	(0.000)	(0.000)	(0.006)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)
Gender: Female	0.057***	0.072***	-2.361	-4.839	0.014**	0.010	-0.015*	-0.017**
	(0.005)	(0.005)	(3.220)	(3.224)	(0.005)	(0.005)	(0.006)	(0.006)
Gender: Male	0.078***	0.087***	-12.740***	-16.922***	-0.006	-0.009*	-0.004	-0.008
	(0.004)	(0.004)	(2.544)	(2.539)	(0.004)	(0.004)	(0.005)	(0.005)
Perceived Quality FE	Yes	No	Yes	No	Yes	No	Yes	No
Month of Rejection	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	125972	125972	74757	74757	74757	74757	74757	74757
R^2	0.066	0.017	0.072	0.024	0.054	0.016	0.066	0.034
Adjusted R^2	0.050	0.016	0.050	0.023	0.031	0.015	0.044	0.033
Note:								*p<0.05; **p<0.01; ***p<0.001

Table S10. *Regression estimates from OLS models predicting publishing outcome with and without control of "Perceived Quality". The reference category is defined as follows: a submission to Journal of Physics D: Applied Physics, desk-rejected in January 2018, with the corresponding author of unknown gender.*

S8. Robustness check: disparities estimated using a subset of peer-reviewed manuscripts and publications identified by an alternative classifier

Among all rejections, 34% are rejected at the peer review stage, indicating that only 34% of rejections receive an expert-evaluated quality assessment, with peer review recommendations in our *Perceived Quality*. It is possible that for most desk rejections, which we categorize with the corresponding *Perceived Quality* of "Round 0", we do not obtain sufficient quality measures. There might also be more variance in quality among these desk rejections. To address this concern, we have also performed analyses on the subsample of rejections that have undergone the peer review process and thus have more accurate quality evaluations. In the regression table below, we observe a quantitatively similar gap between Western and non-Western authors: Western authors are more likely to get their papers published with less delay and effort.

	Published or not	Wait days	Abstract revision	Prob. of author change
Intercept	0.741***	297.877***	0.495***	0.137**
	(0.042)	(25.183)	(0.037)	(0.044)
Western author	0.046***	-17.530***	-0.044***	-0.117***
	(0.006)	(3.440)	(0.005)	(0.006)
Team size	-0.001	-3.127***	-0.009***	0.021***
	(0.001)	(0.624)	(0.001)	(0.001)
Author prior publications	0.000	-0.036***	-0.000	-0.000
	(0.000)	(0.011)	(0.000)	(0.000)
Gender: Female	0.054***	-5.372	0.021*	-0.005
	(0.009)	(5.888)	(0.009)	(0.010)
Gender: Male	0.077***	-14.847**	-0.005	-0.008
	(0.007)	(4.652)	(0.007)	(0.008)
Perceived Quality Fixed Effect	Yes	Yes	Yes	Yes
Month of Rejection	Yes	Yes	Yes	Yes
Observations	42872	25469	25469	25469
R^2	0.095	0.113	0.095	0.118
Adjusted R^2	0.052	0.051	0.031	0.056
Note:				*p<0.05; **p<0.01; ***p<0.001

Table S11. *Regression estimates from OLS models predicting post-rejection publication outcomes for manuscripts only rejected after peer review. The reference category is defined as follows: a submission to Journal of Physics D: Applied Physics, desk-rejected in January 2018, with the corresponding author of unknown gender.*

For a candidate publication identified as the ultimate, we adopt a threshold with highest F1 score (0.857) with recall (0.78) and precision (0.97). For robustness check, we also test another threshold of the classifier with higher recall (0.865), lower precision (0.78) and similar F1 score (0.833).

This threshold enables us to identify more potential publications with plausibly more revision in title, abstract and authorship teams, albeit with reduced accuracy. Thus we obtain a larger sample of reject-and-published paper of 89k. We also find that using the same regression specification, main results of geographical disparities hold similar.

	Published or not	Wait days	Abstract revision	Prob. of author change
Intercept	0.712***	310.186***	0.536***	0.210***
	(0.014)	(9.004)	(0.013)	(0.016)
Western author	0.031***	-24.450***	-0.074***	-0.124***
	(0.003)	(2.149)	(0.003)	(0.004)
Team size	0.005***	-5.023***	-0.013***	0.021***
	(0.001)	(0.350)	(0.001)	(0.001)
Author prior publications	0.000***	-0.019***	-0.000**	0.000
	(0.000)	(0.006)	(0.000)	(0.000)
Gender: Female	0.069***	1.208	0.012*	-0.019***
	(0.005)	(3.238)	(0.005)	(0.006)
Gender: Male	0.085***	-10.269***	-0.011**	-0.007
	(0.004)	(2.557)	(0.004)	(0.005)
Perceived Quality Fixed Effect	Yes	Yes	Yes	Yes
Month of Rejection	Yes	Yes	Yes	Yes
Observations	125972	86383	86383	86383
R^2	0.062	0.070	0.062	0.067
Adjusted R^2	0.046	0.050	0.042	0.047
Note:				*p<0.05; **p<0.01; ***p<0.001

Table S12. *Regression estimates from OLS models predicting post-rejection publication outcomes for manuscripts with the probability of publication predicted by the classifier with higher recall. The reference category is defined as follows: a submission to Journal of Physics D: Applied Physics, desk-rejected in January 2018, with the corresponding author of unknown gender.*

S9. Post-publication outcomes: prestige, revising effort, authorship change and citation counts

We also examine the impact factor of publishing journals and citations for papers rejected and later published elsewhere as additional publishing outcomes.

After controlling for the usual covariates, the difference in ultimate impact factor (IF) between Western and non-Western authors is -0.17 ($P < 0.001$). This suggests that non-Western authors ultimately publish in slightly more prestigious journals than Western authors. The citation is collected as the number of citing papers in the first two years of publication. We find that overall Western authors receive 0.33 fewer citations ($P < 0.001$). However, when we split citations out by self- and external citations, we find that the Western-non-Western gap in external citations is substantively small and of marginal statistical significance (difference=-0.11, P=0.04).

The model is specified the same as our main regression model for measuring the gap between Western and non-Western authors and estimating the .

	IF of publishing journal	External citations	All citations
Intercept	2.459***	1.800***	2.584***
	(0.072)	(0.173)	(0.136)
Western author	-0.169***	-0.113*	-0.331***
	(0.017)	(0.046)	(0.036)
Team size	0.059***	0.117***	0.078***
	(0.003)	(0.008)	(0.006)
Author prior publications	0.000***	0.001***	0.000***
	(0.000)	(0.000)	(0.000)
Gender: Female	0.015	0.240***	0.077
	(0.026)	(0.067)	(0.053)
Gender: Male	0.023	0.622***	0.068
	(0.020)	(0.050)	(0.039)
Perceived Quality Fixed Effect	Yes	Yes	Yes
Month of Rejection	Yes	Yes	Yes
Observations	74757	55689	55689
R^2	0.210	0.117	0.131
Adjusted R^2	0.191	0.093	0.108
Note:			*p<0.05; **p<0.01; ***p<0.001

Table S13. *Regression estimates from OLS models predicting impact factor of publishing journals and self- and external citations. The reference category is defined as follows: a submission to Journal of Physics D: Applied Physics, desk-rejected in January 2018, with the corresponding author of unknown gender.*

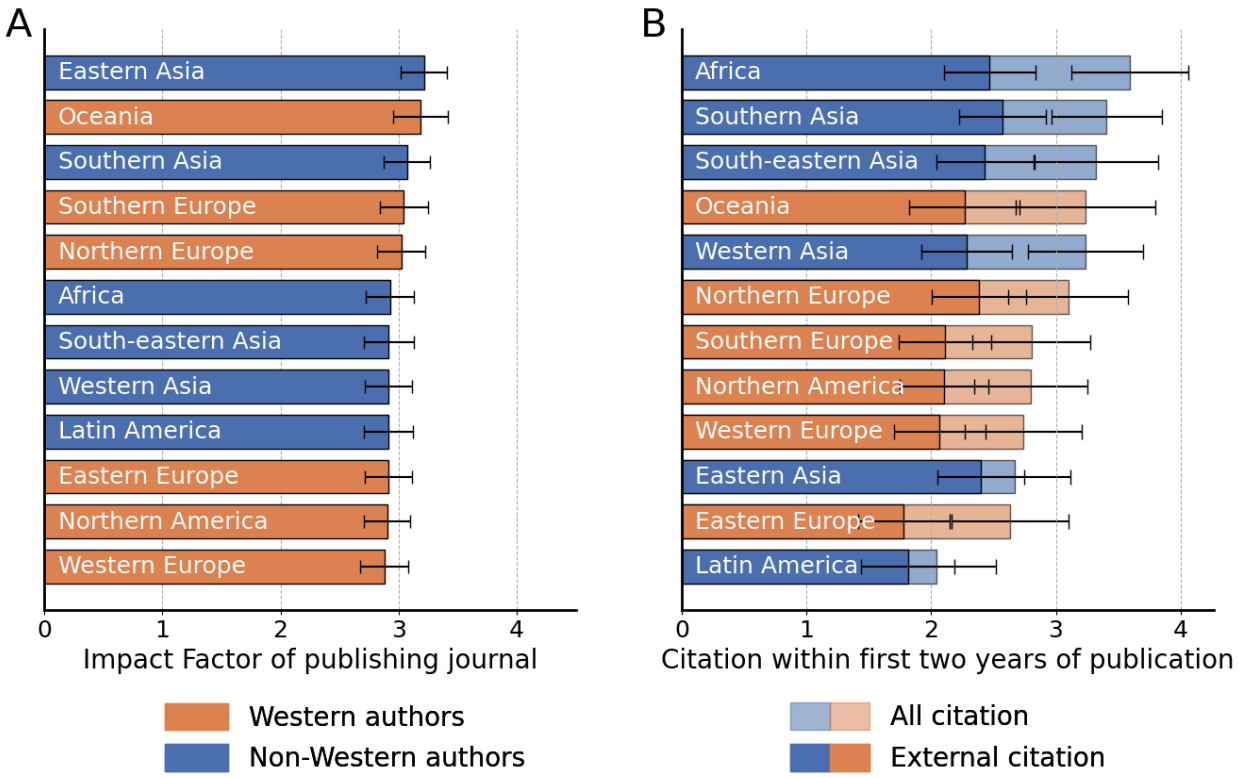


Figure S7*. Estimates from OLS regressions predicting impact factor of publishing journals and self- and external citations as a function of region indicators and the usual set of covariates.*

Besides comparing the proportion of teams experiencing authorship changes, we further investigate the specific outcomes related to authorship changes, including the number of authors joining or leaving the team. Using the same regression model, we find that non-Western authors have a higher number of both authors joining and leaving the team compared to Western authors.

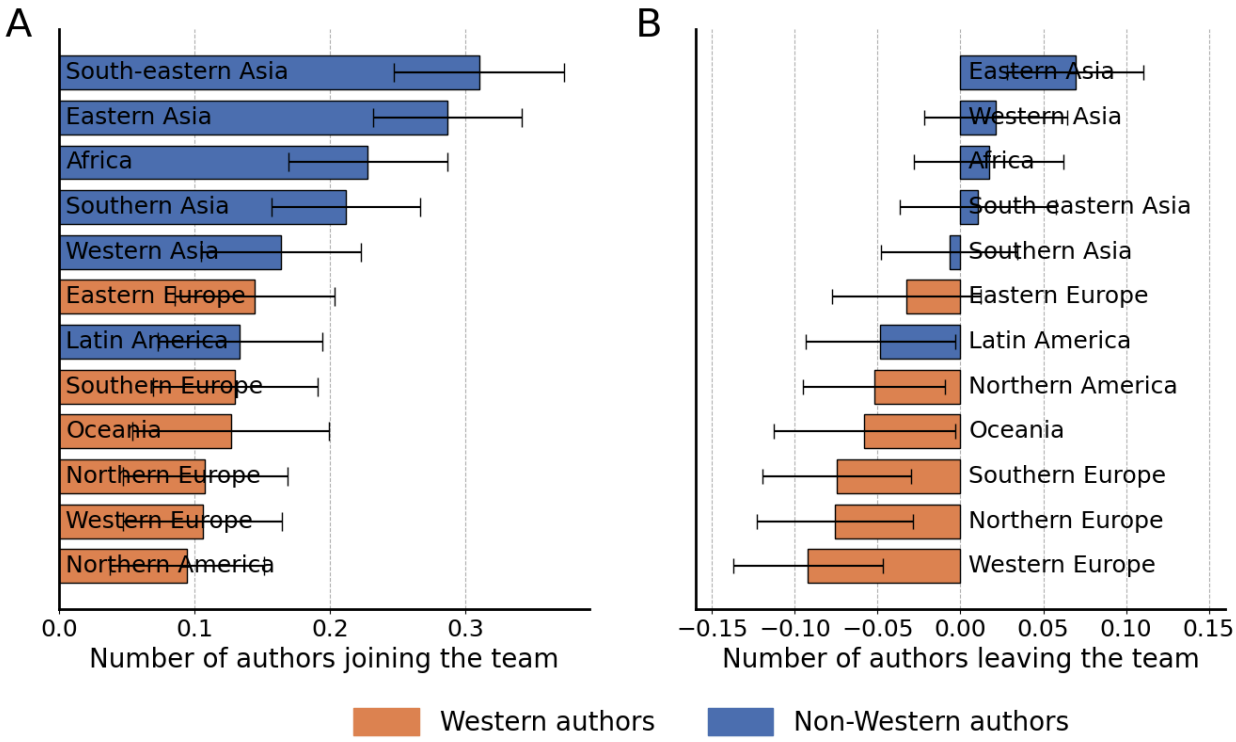


Figure S8. *Regression estimates from OLS models predicting authorship team change measured by the number of authors joining the team and number of authors leaving the team.*

The revision of the abstract text is quantified by the edit distance, which measures the minimum operations required to revise the original abstract of the rejected version to the final published version. This measure captures the overall similarity of content while ignoring word order and repeated words. We also measure semantic similarity, which captures changes of semantic meaning in abstract content, and word jaccard similarity, which evaluates the proportion of shared words to the total unique words for robustness check.

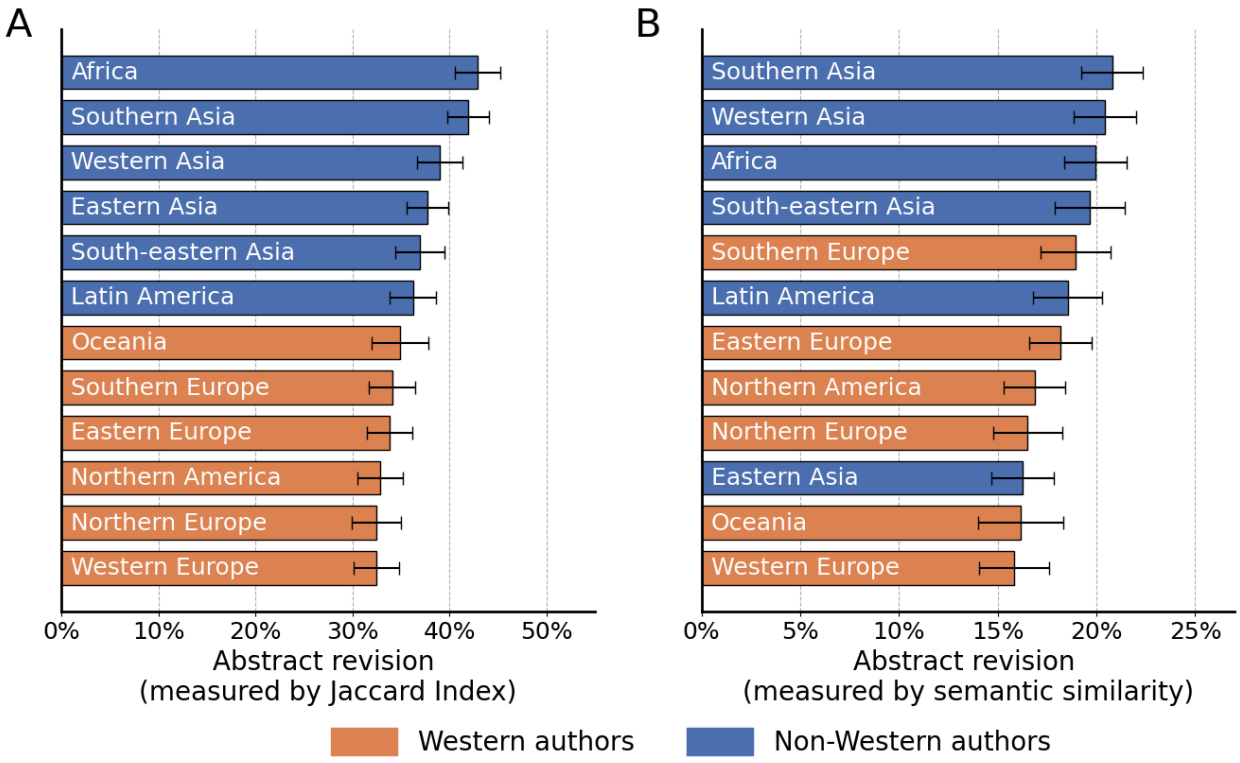


Figure S9. *Regression estimates from OLS models predicting in revision effort measured by abstract token set share (quantified by Jaccard Index) and semantic similarity (quantified by cosine similarity between their SPECTER embedding vectors).*

S10. Suggestive evidence from correlations of publishing outcomes with team size and author seniority

Additionally, we explore the effect of team composition and author seniority on the probability of publication. The model specification and regression results of effect of prior publishing experience are shown as below:

$$If.Published_i = \beta_0 + \sum_j \beta_{1,j} If.Western_j \times Author.Seniority_j + \beta_3 Team.Size_i + \beta_2 Author.Gender_j + \sum_k \beta_{4,k} Month_k + \sum_l \beta_{5,l} Perceived.Quality_l + \epsilon$$

	Dependent variable: Publish or not
Intercept	0.498***
	(0.015)
No prior publication, Wetsern	-0.049***
	(0.011)
One prior publication, Non-Wetsern	0.032***
	(0.008)
One prior publication, Wetsern	0.050**
	(0.016)
Two prior publications, Non-Wetsern	0.071***
	(0.009)
Two prior publications, Wetsern	0.150***
	(0.018)
Ten prior publications, Non-Wetsern	0.137***
	(0.013)
Ten prior publications, Wetsern	0.192***
	(0.022)
Team size	0.007***
	(0.001)
Gender: Female	0.050***
	(0.005)
Gender: Male	0.057***
	(0.004)
Perceived Quality Fixed Effect	Yes
Month of Rejection	Yes
Observations	125972
R^2	0.082
Adjusted R^2	0.066

Note: *p<0.05; **p<0.01; ***p<0.001

A representative selection of 7 out of 214 prior experience categories is shown.

Table S14. *Regression estimates from OLS models predicting probability of publication of authors of different numbers of prior publications. The reference category is defined as follows: a submission to Journal of Physics D: Applied Physics, desk-rejected in January 2018, with the corresponding author from non-Western country, of unknown gender and without prior publication experience.*

The model specification and regression results of effect of team composition are shown as below:

$$If.Published_i = \beta_0 + \sum_j \beta_{1,j} Team.Composition_j \times Team.Size_j + \beta_2 Author.Seniority_i + \beta_3 Author.Gender_j + \sum_k \beta_{4,k} Month_k + \sum_l \beta_{5,l} Perceived.Quality_l + \epsilon$$

	Dependent variable: Publish or not
Intercept	0.642***
	(0.015)
Solo author, Western	-0.149***
	(0.006)
Solo author, Non-Western	-0.147***
	(0.008)
Two authors, Western	-0.013*
	(0.005)
Two authors, Mixed	0.035*
	(0.017)
Two authors, Non-Western	0.066***
	(0.009)
Three authors, Western	0.002
	(0.005)
Three authors, Mixed	0.058***
	(0.012)
Three authors, Non-Western	0.101***
	(0.009)
Author prior publications	0.000***
	(0.000)
Gender: Female	0.051***
	(0.005)
Gender: Male	0.079***
	(0.004)
Perceived Quality Fixed Effect	Yes
Month of Rejection	Yes
Observations	125972
R^2	0.077
Adjusted R^2	0.061
Note:	*p<0.05; **p<0.01; ***p<0.001

A representative selection of 8 out of 90 team composition categories is shown.

Table S15: *Regression estimates from OLS models predicting probability of publication of different team size and composition. The reference category is defined as follows: a submission by a team of four non-Western authors to Journal of Physics D: Applied Physics, desk-rejected in January 2018, with the corresponding author of unknown gender.*

S10. Survey instrument and sample design

Our survey sample, drawn from 2018-2022, was stratified to ensure diverse representation: 40% Western and 60% non-Western authors, 80% peer-reviewed and 20% desk-rejected manuscripts, and 80% manuscripts not published versus 20% that were. The survey, programmed using Google Forms, was distributed via email by the publishing company. It started with basic queries about the author's name, manuscript ID of their rejected submission, and included six multiple-choice questions about their interpretation of the rejection decision and subsequent revision and resubmission behaviors. Participants were also questioned about the current status

of their previously rejected manuscripts, providing a means to validate the reliability of our search algorithms in estimating whether a rejected manuscript has indeed been published. Additionally, we included an optional question asking which factor most influenced their decision regarding the manuscript post-rejection. This aimed to provide insights into the potential motives behind their behavior.

The survey instruments are shown below:

Your publishing strategy with a recently rejected manuscript
First name

_____

Surname

_____

Manuscript ID of rejected manuscript

_____

1. What is the current status of this manuscript?
   - ☐ Not actively revising (have not revised in last 3 months)
   - ☐ Actively revising (revised in last 3 months)
   - ☐ Under review (peer review or editorial review)
   - ☐ Published or in press
   - ☐ Pivoted this project to a different direction
   - ☐ Don't know

1a. If published or in press, in which journal or conference?

_____

1b. If the publication is available online, what is the URL?

_____

2. In your opinion, how negative was the manuscript's assessment in the decision letter?
   - ☐ 1 = Not negative at all (i.e. manuscript is close to publishable as is)
   - ☐ 2
   - ☐ 3
   - ☐ 4
   - ☐ 5 = Extremely negative (i.e. manuscript needs a complete overhaul to be publishable)
   - ☐ Don't know or not applicable

3. In your opinion, how fair was the manuscript's assessment in the decision letter?
   - ☐ 1 = Extremely unfair
   - ☐ 2
   - ☐ 3

- ☐ 4
- ☐ 5 = Extremely fair
- ☐ Don't know or not applicable

4. After rejection, which of the following best describes your very next publishing decision (or plan) on what to do with the manuscript?

- ☐ Abandon manuscript
- ☐ Resubmit to a higher-ranked journal
- ☐ Resubmit to a similarly ranked journal
- ☐ Resubmit to a lower-ranked journal
- ☐ Don't know or not applicable

5. If you resubmitted the manuscript, approximately how much effort and resources did you put into revising? Please quantify the amount in terms of how much effort and resources the rejected manuscript took.

- ☐ Less than 10% of original effort and resources
- ☐ 10 - 25% of original effort and resources
- ☐ 25 - 50% of original effort and resources
- ☐ More than 50% of original effort and resources
- ☐ Don't know or not applicable

6. Which factor had the greatest influence on your decision on what to do with this manuscript after rejection?

_____

S11. Response analysis and matching validation

Out of 278 valid respondents, our findings indicated that we correctly found 142 published papers, with a true positive rate 0.51. But, it mistakenly marked 41 papers as published when they weren't, which is a false positive rate of 0.15. We also missed 75 papers that were published, giving a false negative rate of 0.27, and correctly identified 22 papers as not published, showing a true negative rate of 0.08.

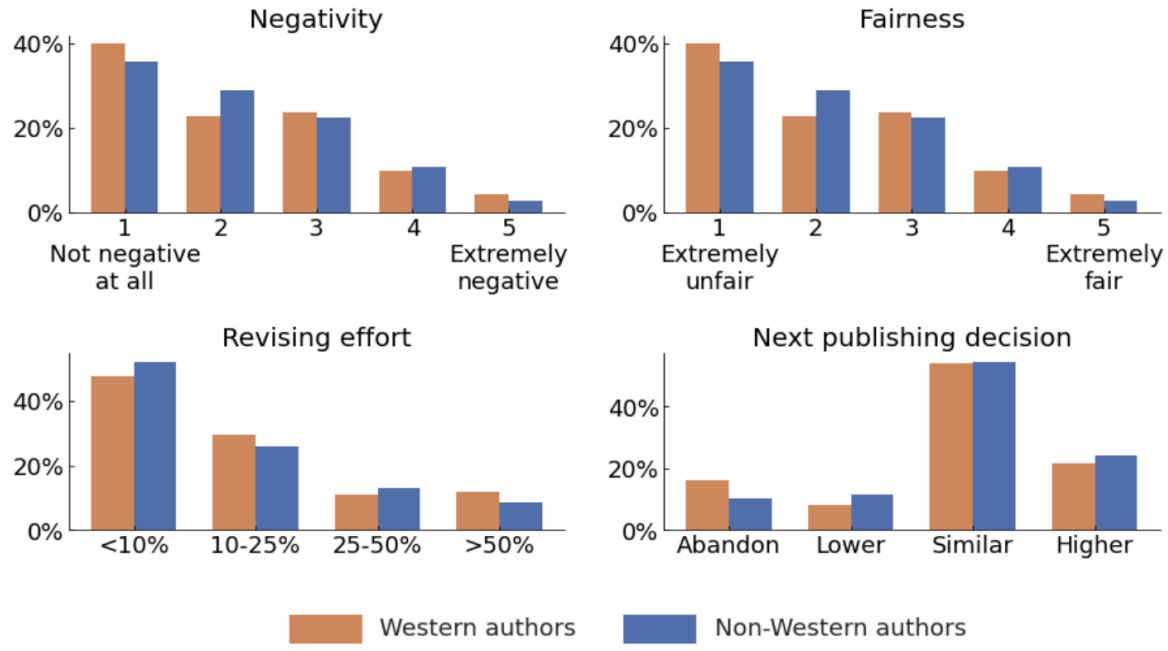


Figure S10. *Distribution of survey responses. The raw data didn't show a significant difference between Western and non-Western authors.*

We compare the statistics between the respondent and non-respondent groups to examine potential bias in the survey. We observe an imbalance, with 62% of the respondents being from Western countries compared to 38% in the non-respondent group. This disparity may contribute to the null effect observed in our regression results.

Covariate	Respondents(N=278)	Non-respondents(N=9722)	Diff.-in-means	p-value
If western(%)	62.1	38.4	23.7	0.0
Journal IF	2.92	3.46	-0.54	0.0
Number of Pub	33.7	46.1	-12.4	0.0
Number of rounds	0.08	0.06	0.02	0.0
Date of rejection	809.7	739.1	70.6	0.0
Team size	3.39	4.35	-0.96	0.0
Gender(%)	73.2	59.5	13.7	0.0

Table S16. *Covariate balance table for selection into survey response.*

We use OLS model with the following specifications:

$$Survey.Response_i = \beta_0 + \beta_1 If.Western_i + \beta_2 Author.Seniority_i + \beta_3 Author.Gender_i + \beta_4 Team.Size_i + \sum_j \beta_{5,j} Month_j + \sum_k \beta_{6,k} Perceived.Quality_k + \epsilon$$

The regression results are presented as below:

	Negativity	Fairness	Revising effort	Next decision
Intercept	3.600***	2.120***	1.459***	2.332***
	(0.639)	(0.530)	(0.431)	(0.380)
Western authors	-0.020	-0.009	-0.036	-0.156
	(0.257)	(0.214)	(0.188)	(0.158)
Team Size	0.015	0.073	-0.021	-0.012
	(0.058)	(0.047)	(0.039)	(0.034)
Author prior publications	0.003	-0.002	-0.003	-0.001
	(0.003)	(0.003)	(0.002)	(0.002)
Gender: Male	-0.662*	-0.208	0.018	0.115
	(0.333)	(0.274)	(0.238)	(0.194)
Gender: Female	-0.771	-0.280	-0.225	0.041
	(0.497)	(0.410)	(0.341)	(0.296)
Perceived Quality Fixed Effect	Yes	Yes	Yes	Yes
Month of Rejection	Yes	Yes	Yes	Yes
Observations	211	225	207	226
R^2	0.410	0.346	0.467	0.408
Adjusted R^2	0.068	-0.004	0.148	0.093
Note:				*p<0.05; **p<0.01; ***p<0.001

Table S17. *Regression estimates from OLS models predicting four aspects of procedural knowledge of survey respondents. The reference category is defined as follows: a submission to Journal of Physics D: Applied Physics, desk-rejected in January 2018, with the corresponding author of unknown gender.*