You do not receive enough recognition for your influential science

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Abstract

During career advancement and funding allocation decisions in biomedicine, reviewers have traditionally depended on journal-level measures of scientific influence like the impact factor. Prestigious journals are thought to pursue a reputation of exclusivity by rejecting large quantities of papers, many of which may be meritorious. It is possible that this process could create a system whereby some influential articles are prospectively identified and recognized by journal brands but most influential articles are overlooked. Here, we measure the degree to which journal prestige hierarchies capture or overlook influential science. We quantify the fraction of scientists' articles that would receive recognition because (a) they are published in journals above a chosen impact factor threshold, or (b) are at least as well-cited as articles appearing in such journals. We find that the number of papers cited at least as well as those appearing in high-impact factor journals vastly exceeds the number of papers published in such venues. At the investigator level, this phenomenon extends across gender, racial, and career stage groupings of scientists. We also find that approximately half of researchers never publish in a venue with an impact factor above 15, which under journal-level evaluation regimes may exclude them from consideration for opportunities. Many of these researchers publish equally influential work, however, raising the possibility that the traditionally chosen journal-level measures that are routinely considered under decision-making norms, policy, or law, may recognize as little as 10-20% of the work that warrants recognition.

Introduction

Biomedical hiring and promotion committees use journal-level heuristics because the quantity of documentation that researchers provide in their applications exceeds the attentional capacity that reviewers can provide (1). Ideally, scientific experts would read and apply their scientific expertise to each article under consideration for a given decision about hiring, promotion, or resource allocation (1, 2). In some settings, this ideal may be possible, however, in many settings it is not feasible. For example, tenure-track job advertisements often attract hundreds of applicants, each with dozens of relevant publications to assess. In such a case, the biomedical research community recommended the inclusion of quantitative indicators, but ones that reflect information specific to the articles under consideration, not the venues in which they appear (1).

One sensibility that often resonates with members of the scientific community that if we recognize papers during personnel advancement based in large part on the citation rate of their venue, we should also recognize papers cited equally well even if appearing in less prestigious venues (3). If we recognize a paper published in Cell, we should also recognize papers in lower-tier journals that

were recognized by practitioners in the field and cited equally well. However journal-level metrics fail to identify up to 90% of the equally well-cited papers in the biomedical research literature, controlling for field and year of publication (4). In other words, the recall of the biomedical community's chosen measure of meritorious papers is on the order of a dismal 10%.

Here, we measure the degree of misallocation of recognition based on the exclusive use of journal-level metrics at the level of individual articles and investigators. We use a common approach, impact factor thresholding (5), to identify papers published in prestigious venues ("Journal Elite") as well as those that are equally well-cited ("Citation Elite" papers) but published in any journal. We use a journal citation rate (hereafter referred to as "impact factor") of 15 citations per article per year as our main threshold, but test 10 and 20 citations per paper per year as well for robustness checks. We find that the number of papers that would receive recognition using article-level metrics instead of journal-level metrics is several-fold. Half of biomedical researchers have never published in an elite journal, but a large fraction of these have published equally well-cited papers.

Results

Journal metrics overlook most influential science

In a previous study, we asked how many highly influential papers are actually published in the most prestigious journals such as Science, Nature, and Cell (4), using the Relative Citation Ratio (RCR), an article-level citation indicator that controls for field and year of publication (3, 4, 6-8). We showed that there are nearly ten times more papers that are as highly cited as those in prestigious venues such as Cell, Nature, and Science, but that appear in less prestigious venues. This result raises the alarming possibility that, in identifying influential papers exclusively based on the prestige of the journal in which they appear, research assessment overlooks the vast majority of equally influential articles. However, the number of overlooked influential articles may depend on the precise journal citation rate threshold chosen to identify "prestigious" journals.

In order to test the robustness of this finding, here we varied the impact factor threshold used to identify a journal as "prestigious" or not. We determined the median RCR of papers published in journals matching or exceeding the chosen impact factor threshold (impact factor >= 15, "Journal Elites"). Articles with an RCR higher than the median of those published in journals above the impact factor thresholds were labeled as article-level "Citation Elites" (Figure 1A-B). Throughout this paper, we assess robustness of findings to different choices of impact factor thresholds and find them to be generally invariant (Supplemental Materials). We find that the vast majority of influential papers are published in journals below the impact factor threshold defining "prestigious" (Figure 1C). This result raises a question: where are these other influential papers published? The modal response depends slightly on the impact factor threshold used to define "prestigious", but in general, such highly influential papers are published in journals with lower impact factors (Figure 1C). Furthermore, the more restrictive the impact factor threshold one uses, the fewer Citation Elite papers are recognized using journal-level measures (Figure 1D).

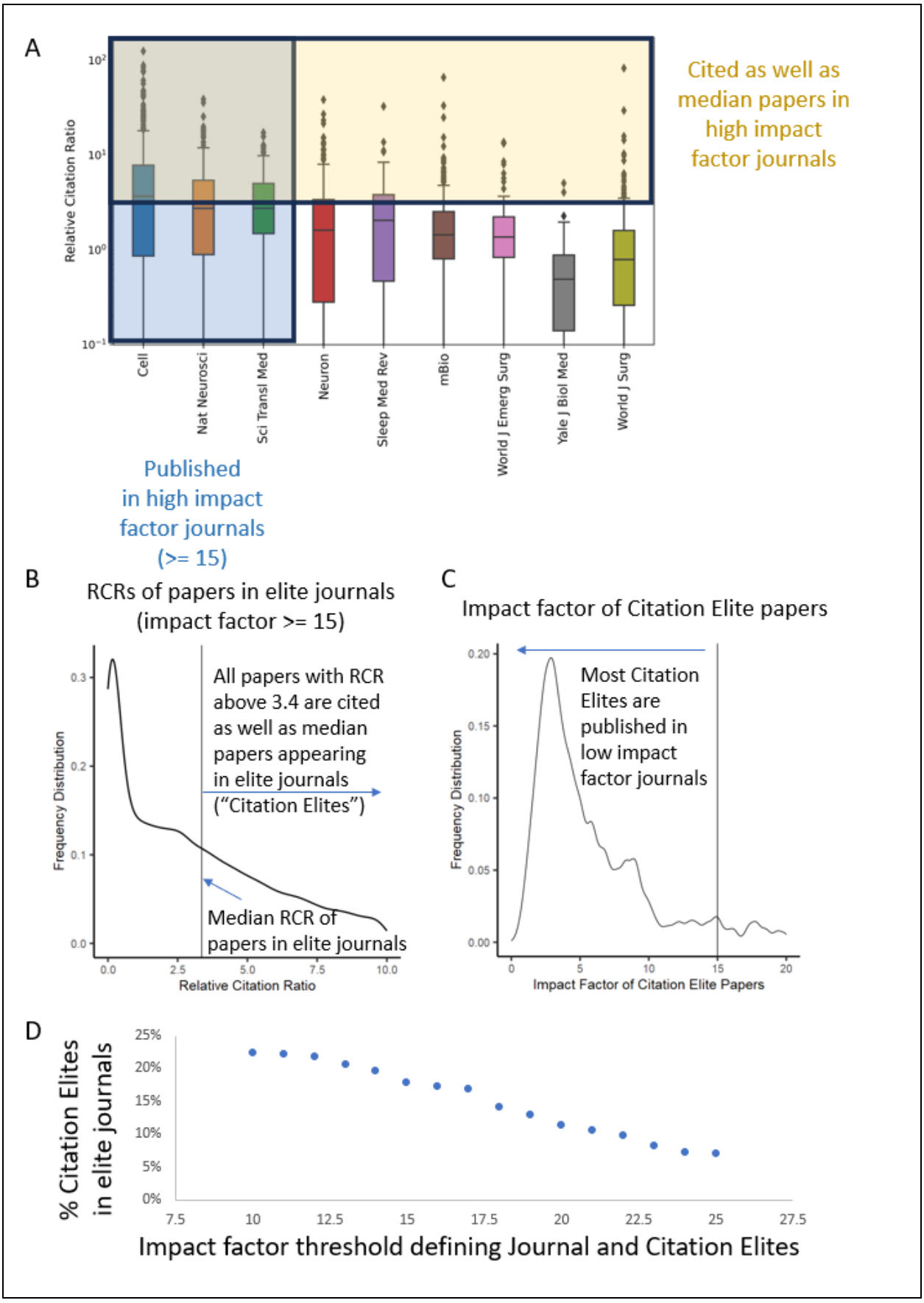


Figure 1. Most influential papers are published in lower-impact factor journals. (A) Schematic for determining which papers are as highly cited as those in prestigious journals. Box and whisker graphs of the RCR of papers from three journals above the selected impact factor threshold are shown (left, blue shading, "Journal Elites") alongside similar graphs for journals with subthreshold (< 15 citations per paper per year) are shown to the right. Articles with RCR's above the line (yellow shading) are considered Citation Elites. All of these journals published multiple Citation Elites. (B) Distribution of article-level Relative Citation Ratios for papers published in elite journals (impact factor >= 15). (C) Impact factor of journals where Citation Elite papers were published. Most papers that are as well cited as those in impact factor >= 15 journals are in fact published in lower-impact factor journals. (D) Generalization of the findings in (C) across different impact factor thresholds. The more stringent the threshold to define an elite journal, the more Citation Elites are published among lower-impact factor journals.

Incorporating Citation Elite papers into evaluation benefits the vast majority of authors

To evaluate how these article-level results generalize to investigator-level indicators, we turned to publicly available, author-level profiles published by the National Center for Biotechnology Information (NCBI) (9). Biomedical investigators have the opportunity to generate an opt-in public publication profile that can also be used to populate their most relevant publications on NIH biosketches while they apply for funding. We downloaded 50422 publicly available publication profiles from NCBI in 2022 that matched to NIH-funded investigators, ranging from graduate fellows to late-career investigators (Figure 2). We focused on researchers that published at least one article in recent years (i.e. 2010-2019) to exclude artifacts from investigators that left the biomedical research workforce prior to 2010.

The use of journal level metrics is historically pervasive and entrenched in biomedical research hiring and promotion decisions (1, 2). How might this change if the community also recognized Citation Elite papers? The fraction of scientists that have a higher number of Citation Elite papers vs. Journal Elite papers is nearly an order of magnitude higher (Figure 2). This suggests a substantial improvement to recognition for a large segment of the biomedical research workforce by including article-level indicators as a way of recognizing research.

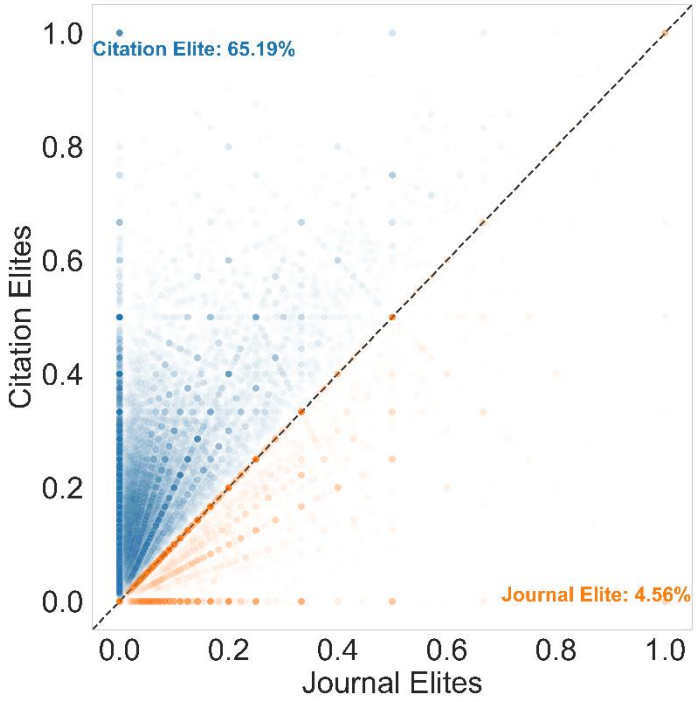


Figure 2. Scatter plot of the fraction of each researchers' publications (each dot is one researcher) that are above the journal impact factor threshold (x-axis) vs. those that are above the corresponding article-level citation threshold (y-axis). Researchers above the line would receive more recognition using article-level metrics (hereafter labeled as Citation Elite) while those below the line would receive more recognition using journal-level metrics (hereafter referred to as Journal Elite). Numbers do not add to 100% because some scientists publish no papers that would fall into the Journal Elite or Citation Elite categories.

Who benefits from article-level recognition?

Structural barriers to equality in the biomedical research workforce have traditionally favored scientists who are more senior, white, or men (2, 16, 18). We asked whether historically underrepresented groups likewise receive more recognition using article- vs. journal-level metrics. We therefore examined the distribution of demographic characteristics of those scientists who receive more recognition using journals vs. articles (see Methods). Overall, 65.19% of researchers would receive more recognition using article-level metrics, while a vastly smaller 4.55% would using journal-level metrics. Of those who receive more recognition with journal metrics 69.53% were men while 30.47% were women (Figure 3). By contrast, of those who would receive more recognition with article metrics 62.28% were men while 37.7% were women (Figure 3), much closer to the overall distribution of men and women in this dataset (38.87% female) (Figure 3). By comparing metrics for men and women in absolute, rather than relative terms, we observe that 18.43-fold more women and 13.34-fold more men receive more recognition with article-level metrics (Figure 3 and Supplemental Table 5).

Figure 3. Demographic analysis of scientists who receive more recognition with journal- vs. article-level measures. (Top, within box) Breakdown of how many scientists filtered by those who have more Citation Elite (these scientists are labeled as Citation Elites) papers than Journal Elite papers (labeled as Journal Elites) are male vs. female. Black line, actual number of male vs. female scientists in this dataset. (Top, outside box) Breakdown of how many scientists filtered by gender receive more recognition with article-level citations (Citation Elite) vs. journal impact factor (Journal Elite). (Middle) Breakdown filtered by race. (Bottom) Breakdown filtered by seniority.

We next examined the same effects stratified by race. The vast majority of scientists, regardless of race, would receive more recognition using article-level metrics (Figure 3). Statistical analysis confirmed that this is a highly significant effect (Chi-sq $p < 7.9e-11$, Supplemental Tables). The phenomenon of receiving more recognition with article-level measures appears to be broadly shared across racial groups. Recent work suggests that applying thresholding to imputed racial

predictions as we do here could in principle amplify class imbalances inherent in the data (10-12). We therefore confirmed our results on continuous racial prediction scores and found similar results (Supplemental Figure 1).

Finally, we examined the relationship of career stage and the differences between researcher recognition with journal- and article-level metrics (Figure 3 and Supplemental Materials). As we observed with racial demographics, improvements in recognition are broadly shared across early, mid, and senior career stages.

Reexamination under strict zero-sum conditions

If article-level measures were considered instead or in addition to journal-level measures, would any career advancement benefit be gained? After all, competition for resources that enable research is often framed as zero-sum, whereby researchers are ranked by correlates of merit and some percentage selected. Under a zero-sum framework, it would be expected that there should be no proportional differences for recognition of researchers on the basis of article-level metrics vs. journal-level metrics, as each person better-recognized under one measure would be replaced by someone better-recognized under the other. Surprisingly, we still observe large differences between researchers labeled as Citation Elites vs. Journal Elites, even when using rank-ordered metrics that are ostensibly zero-sum. Many more researchers published rank-ordered Citation Elite papers than published rank-ordered Journal Elite papers (47.1% vs. 27.8%).

For ranked continuous data, this result should not be possible. Instead the proportions should each be 50%. To investigate this phenomenon further, we turned to the probability distributions of the raw and rank-ordered statistical distributions. (Figure 4). The distribution of scores is skewed for both journal-level metrics and article-level metrics (Figure 4A-B), but the Citation Elite frequency distribution has a fatter tail, indicating more researchers publish such papers, consistent with the previous results. Rank-ordering the data should convert these data into uniform statistical distributions, and this property is what aligns the data with a zero-sum competition framework. For much of the probability distribution (Figure 4C-D), we see that this is the case. However, in both datasets, we observe that there is zero-inflation. In other words, for each indicator, some number of researchers never publish Journal or Citation Elite papers. However, the degree of zero-inflation differs greatly for Journal and Citation Elites. (Figure 4C-D). Vastly more scientists receive recognition for their influential work when examining article-level indicators than journal-level indicators.

Even using rank-order data that aligns with a zero-sum competition framework, we observe that, in general, researchers are much more frequently recognized using article-level indicators (Figure 5). We observe a similar gender difference favoring article-level metrics using the rank-ordered data as we observed using the continuous data. Likewise, we observed that each gender, racial group and career stage in general would receive more recognition with article-level indicators (Figure 5). Thus, even under a nominally zero-sum framework, diverse researchers would receive more recognition using article-level indicators. A large minority of researchers who would never receive recognition using journal-level thresholding would receive consideration if article-level indicators were included (Figure 6). We observe that the artificial scarcity of recognition in a journal-level framework impacts a sizeable minority, if not the outright majority of biomedical researchers.

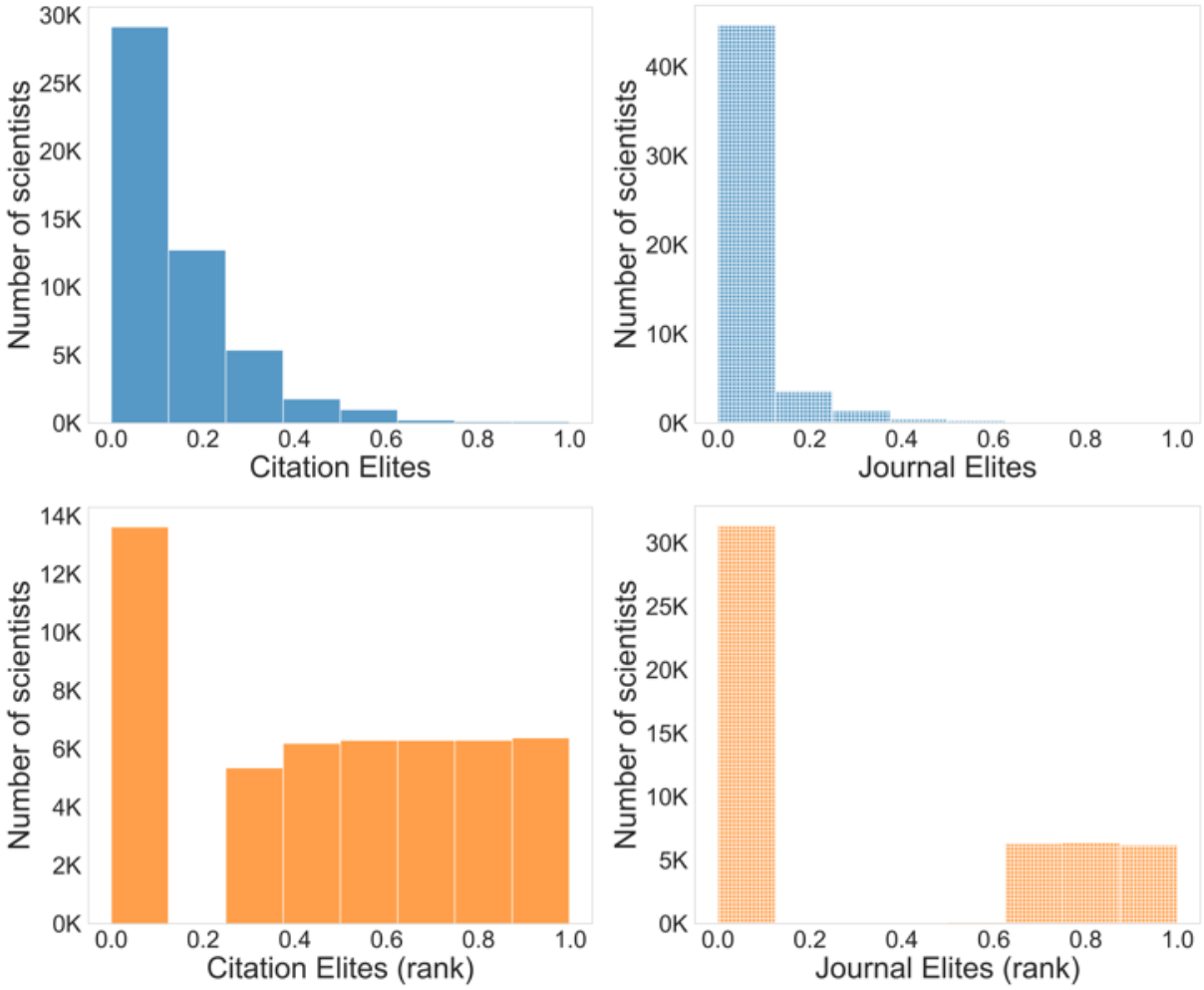


Figure 4. Distributions of researcher recognition. (A, B) Frequency distributions of the fraction of each researcher's publications that are recognized under article-level (A, "Citation Elites") vs. journal-level metrics (B, "Journal Elites"). (C, D) Frequency distributions after rank-ordering to align the scores with a zero-sum framework using article-level (C) vs. journal-level metrics (D). In principle, rank-ordering should flatten these into uniform distributions, but there is a high degree of zero-inflation. Approximately half of researchers have zero publications in prestigious journals (D, left). By contrast, only a quarter of researchers do not have articles that are cited as well as those published in prestigious journals (C, left).

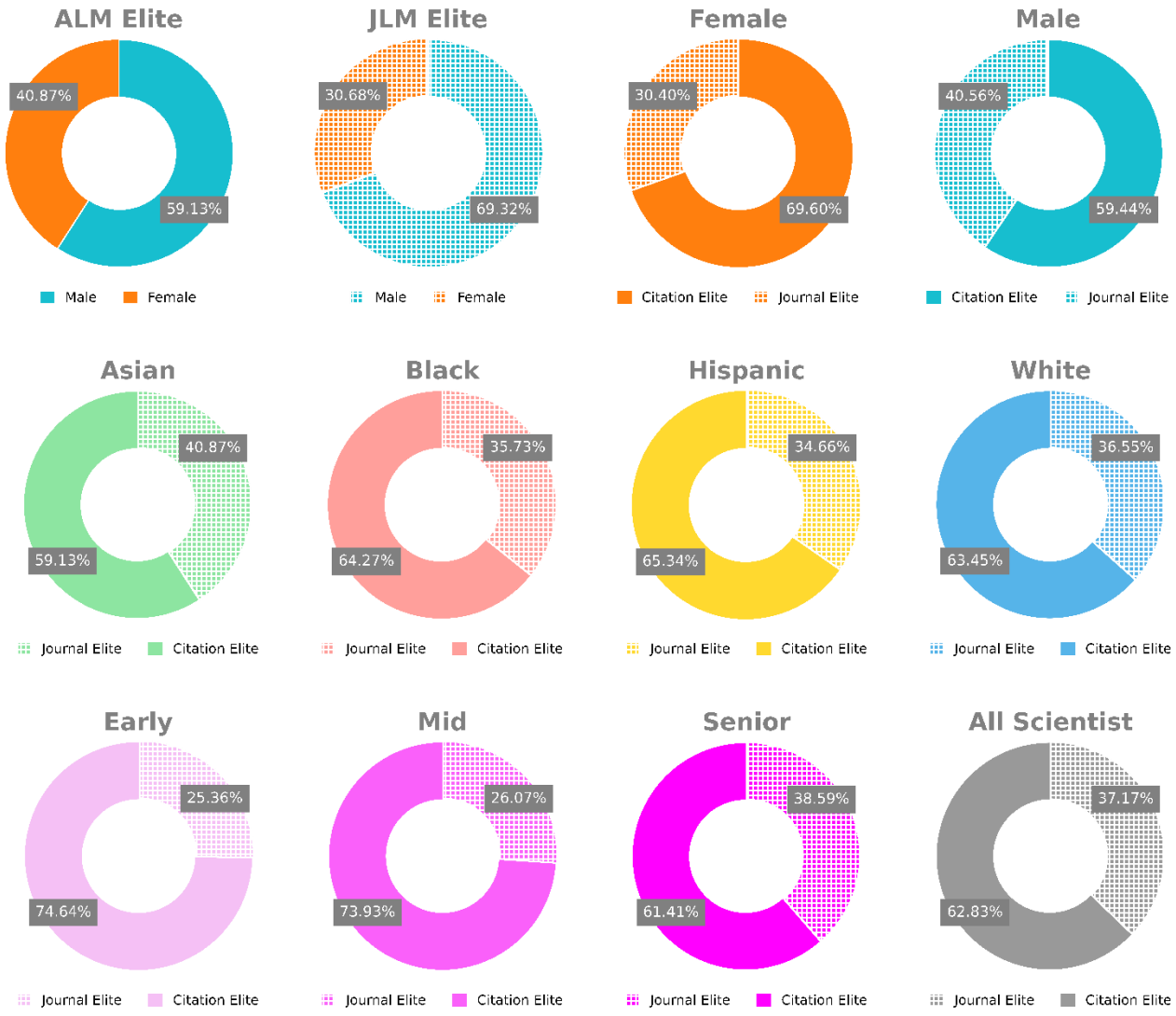


Figure 5. Demographic analysis of scientists who receive more recognition with journal- vs. article-level measures using zero-sum rankings. (Top) Breakdown by gender. (Middle) Breakdown by race. (Bottom) Breakdown by seniority.

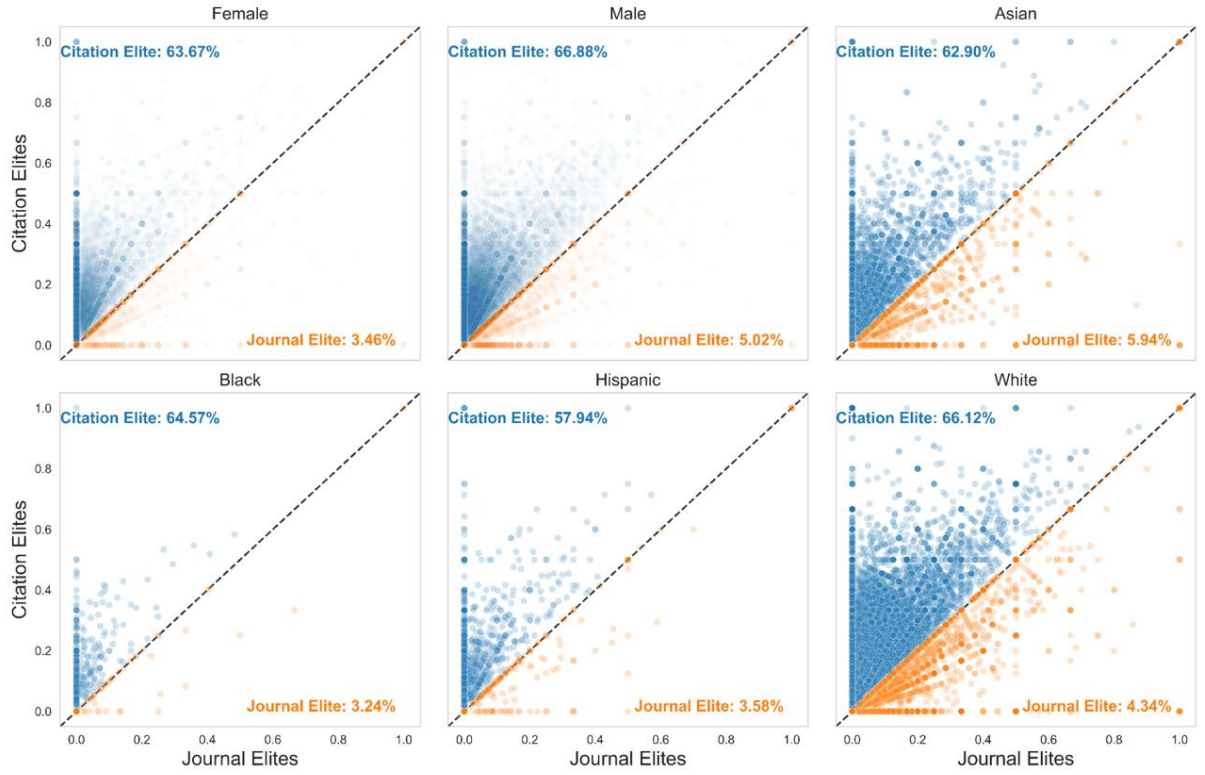


Figure 6. Scatter plots of the fraction of researchers' papers are Journal Elite (x-axis) vs. Citation Elite using rank-ordered data (rather than raw data) consistent with zero-sum analysis (y-axis), stratified by gender or race.

Discussion

In this study, we measured the degree of misallocation of recognition based on the exclusive use of journal-level metrics at the level of individual investigators vs. the alternative of including article-level indicators as recommended by the scientific community (1). We find that, using a variety of impact factor thresholds, researchers overwhelmingly receive more recognition with article-level indicators. This advantage cuts across racial, gender, and career groups. Even under zero-sum conditions, we observe that many more researchers would receive recognition using article-level indicators vs. journal-level indicators. This is because most researchers never publish in a "prestigious" journal as operationalized by impact factor thresholds, but many published papers in lower impact factor journals are as highly cited as those appearing in these journals.

In 2013, signatories to the San Francisco Declaration on Research Assessment acknowledged the pervasive harm that the continued use of journal-level heuristics in funding, hiring, and promotion decisions causes to scientists (1). This mental heuristic is akin to judging a paper by the company it keeps (the average citation rate of all the other papers published in the journal) rather than by the article's own downstream influence. Signatories acknowledged that, while the use of scientific judgment about a paper is the gold standard, in many decision-making contexts where there are potentially thousands or millions of scientific articles to compare, it is necessary

to augment expert judgment with metrics. These should be article-level to ensure that the information is specific to the article(s) in question, rather than by the company they keep.

Challenges in maintaining a sustainable biomedical research workforce in the United States have concerned scientists and policymakers alike for years. The workforce has been skewing older for decades (13, 14), underrepresents African American/Black (AA/B) researchers (15-17), and has traditionally been male-dominated (18-20). These trends have exacerbated concerns about the sustainability of the U.S. biomedical research workforce. These topics have been discussed at congressional appropriations hearings (21), motivated specific appropriations for the National Institutes of Health (NIH) in the 21st Century Cures Act (14), and have been the subject of written testimony from NIH leadership to Congress (22). NIH Initiatives such as the Next Generation Research Initiative and Faculty Institutional Recruitment for Sustainable Transformation initiative have attempted to address some of these workforce problems (23, 24). However, the scientific community bears some responsibility for addressing structural problems, especially since many of the norms and potential policy levers that could address such challenges exist outside the direct influence of funding agencies' policymaking. The San Francisco Declaration on Research Assessment (DORA) attempted to address one such structural problem: the inappropriate use of journal-level metrics like the Journal Impact Factor that, because of online journals' artificial scarcity, severely limits the number of researchers who receive such prestigious signals on their track records (1). Journal-level metrics tend to favor more established, male, and white investigators (15, 17), potentially amplifying structural inequalities in the workforce.

The underrepresentation of women in prestigious journals is well documented (18, 25). This disparity can be attributed to several factors, including explicit and implicit bias (25), gendered patterns within research fields (26, 27), as well as limited access to resources and opportunities for publishing in esteemed journals (19, 28). Consequently, the barriers faced by women in publishing in these journals result in unfavorable evaluations based on journal-level metrics. Given the consequence of such evaluation, female researchers would be further disadvantaged. Therefore, our research findings offer further evidence that the utilization of article-level metrics may contribute to addressing the broader gender disparity issues within the scientific workforce.

Many researchers in the biomedical community feel that they are unfairly judged in research assessment; that they do not receive enough credit given the influence on the research community of their published work (29). We find strong empirical evidence that this is the case; by quantitatively comparing the fraction of researchers who receive recognition using the impact factor thresholds associated with their papers vs. the number of papers cited at least as well as papers published in such journals, we find several-fold difference between the two. The majority of researchers would receive more consideration using article-level compared to journal-level metrics. This result extends to all examined racial groups, career stages, and genders, and is especially true for women. The artificial scarcity of recognition enforced by a journal prestige system built on the perception of exclusivity quantitatively and systematically dismisses the influential work published by, at the minimum, tens of thousands of influential scientists.

Methods

Publication profiles

Publicly available data on funded NIH grants were downloaded in bulk from NIH ExPORTER (30). From these, names of principal investigators (who could be graduate students on training grants through senior investigators funded on long-term research project grants) were extracted. From these names, those investigators who opted in to posting a public publication profile on MyNCBI (9) were crawled using the MyNCBI URL structure that incorporates the name representation found in NIH ExPORTER data. PubMed (31) identifier numbers for Medline papers were extracted from those public sites to construct a profile of each researcher's publications. The publicly available WRU (32) and gendeR (33) R packages were used for race and gender imputation. We define the early career researchers as those who have a career age of five years or less and mid-career researchers as those who have a career age of ten years or less but more than five (34). The rest are categorized as senior researchers.

Identifying prestigious articles using journal- and article-level metrics

Biomedicine has long recognized papers published in prestigious venues as influential. Many have advanced the view that papers that are as highly cited as those appearing in such prestigious journals should also be recognized as influential. We used a common heuristic, impact factor thresholding (5), to identify papers published in prestigious journals (i.e. using an impact factor threshold of 15, papers published in journals with an impact factor of 15 or more would be recognized as influential in a journal-level recognition regime). We used the journal citation rate in the iCite database as our measurement of impact factors (4, 6, 35-39).

Under the sensibility that papers that are as highly cited as those appearing in such prestigious journals should also be recognized as influential, we used the NIH Relative Citation Ratio (RCR) (4, 6), which measures influence as the number of citations per year an article has received, accounting for its field of research and publication year.

For a given impact factor threshold, articles were flagged as influential using journal-level metrics ("Journal Elites") if they were published in a journal whose impact factor exceeded the chosen threshold in the year of the article's publication.

For article level metrics, the following procedure was used to identify papers recognized as influential ("Citation Elites") as those in a prestigious journal selected by the given impact factor threshold:

1. Identify papers published in a journal whose impact factor exceeded the chosen threshold
2. Measure the median RCR of papers published in these high impact factor journals (RCR_{med})
3. Flag as influential any paper exceeding RCR_{med}

Data Collection

For this analysis, we pulled 50422 publicly available author profiles from National Center for Biotechnology Information (NCBI) in 2021 that matched NIH-funded investigators. For each author, we extracted the following features to conduct our analysis:

start year(int64): The year with the earliest publication of the author as per the database record

end year(int64): The year with the latest publication of the author as per the database record

decade(int64): The decade of the earliest publication of the author

article level metric(float64): fraction of papers of the author that has rcr equal to or higher than the median rcr of papers published above the specific JIF threshold

journal level metric(float64): fraction of papers of the author that meet or exceed the specific impact factor threshold

article level metric_rank(float64): percentile rank of article level metric

journal level metric_rank(float64): percentile rank of journal level metric

rcr_median(float64): median rcr of the papers with

appl(int64): application id associated with the name from the database

surname(object): the surname of the author

forename(object): the forename of the author

forename_longest(object): for multiple forenames, the one with the most characters

male(float64): proportion of male names based on U.S. census data with the forename_longest of the author using R's gendeR package

female(float64): proportion of female names based on U.S. census data with the forename_longest of the author using R's gendeR package

gender(categorical): defined based on the largest of male and female

white(float64): the probability of being white inferred from surname using R's wru package

black(float64): the probability of being black inferred from surname using R's wru package

his(float64): the probability of being Hispanic inferred from surname using R's wru package

asi(float64): the probability of being Asian inferred from surname using R's wru package

oth(float64): the probability of being anything other than white, black, hispanic, and asian inferred from surname using R's wru package

gender(categorical): defined based on the largest of the race probabilities

art_better(bool): Binary class for whether a researcher appears more competitive under article level metric compared to journal level metric

journ_better(bool): Binary class for whether a researcher appears more competitive under journal level metric compared to article level metric

art_journ_same(bool): Binary class for whether journal level metric equals to article level metric

Supplemental Materials

Statistical Analysis

Threshold	chi sq statistic	p-value
10	61.77	3.842834850588465e-15
15	40.57	1.8922670956226282e-10
20	9.87	0.0016

Supplemental Table 1: Chi sq test on gender (all 3 thresholds showed significance): We used python's stats module from scipy library and python 3.8.8 version for the Chi-square test.

Threshold	chi sq statistic	p-value
10	96.81	7.510471124857204e-21
15	50.026	7.887060421743808e-11
20	30.8199	9.275798428124219e-07

Supplemental Table 2: Chi-square test on race: We used python's stats module from scipy library and python 3.8.8 version for the Chi-square test. We classified each scientist in a particular race if the probability of the researcher being in that racial group is greater than 0.50.

Career Stage	P-value
Early	9.049375221567279e-75
Mid	0.0
Senior	0.0

Supplemental Table 3: Paired sample t-test on Citation Elites vs Journal Elites based on career stage: We conducted a matched-pair t-test for each career stage across all the thresholds. We used python's stats module from the scipy library and the python 3.8.8 version for the test. We define early career researchers as those who have a career age of five years or less and mid-career researchers as those who have a career age of ten years or less but more than five. The rest are categorized as senior researchers.

	Asian	Black	White	Hispanic
Journal Elite	495	16	1687	65

Citation Elite	5244	319	25713	1051

Supplemental Table 4. Investigators stratified by race whose papers are most frequently recognized in the Journal Elite vs. Citation Elite categories. Chi sq table for race at an impact factor threshold of 15. Chi-sq: 50.026, p value: 7.8870604217438O8e-11

	Female	Male
Journal Elite	592	1351
Citation Elite	10909	18017

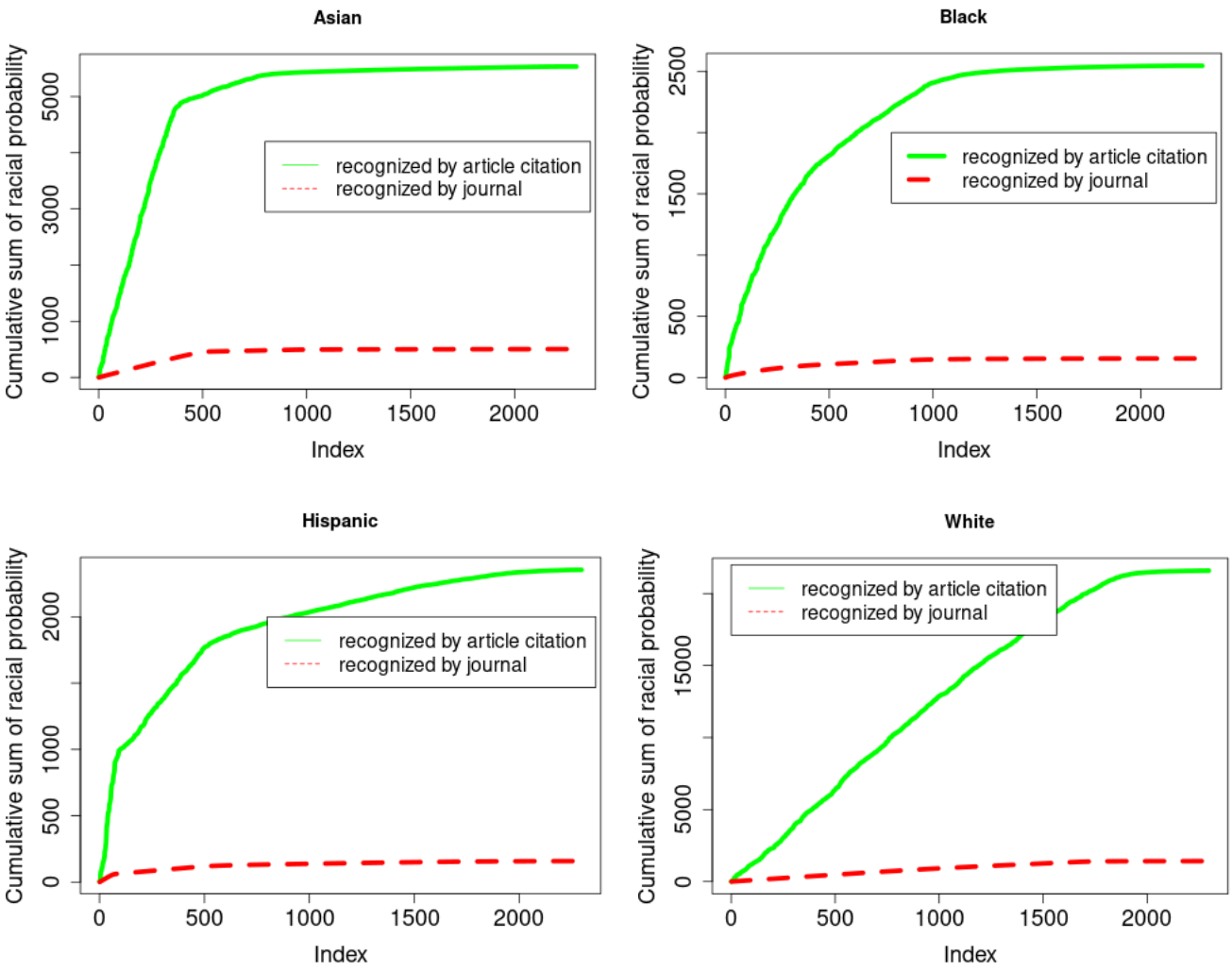
Supplemental Table 5. Investigators stratified by gender whose papers are most frequently recognized in the Journal Elite vs. Citation Elite categories. Chi sq: 40.575, p value: 1.8922670956226282e-10

	Early	Mid	Senior
Journal Elite	71	201	2026
Citation Elite	717	2813	29341

Supplemental Table 6: Investigators stratified by career stage whose papers are most frequently recognized in the Journal Elite vs. Citation Elite categories. Chi-sq: 8.289, p-value: 0.0158.

Threshold (Impact Factor 15+)	p-value
Asian	< 2.2e-16
Black	< 2.2e-16
Hispanic	< 2.2e-16
White	< 2.2e-16

Supplemental Table 7: KS Test on Racial Probability:
We conducted 2-sided k-s test on each racial probability score for scientists who receive more recognition under article vs journal-level metrics (also see Supplemental Figure 1). The p-value of the k-s test is significant across all three thresholds (impact factor >= 10, 15, or 20, respectively).



Supplemental Figure 1: Cumulative probability distribution of racial score of scientists who are more recognized as Citation Elites vs. Journal Elites. p-values shown in Supplemental Table 7.

Acknowledgements

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