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Measuring Science: Performance Metrics and the Allocation of Talent†

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We study how performance metrics affect the allocation of talent by exploiting the introduction of the first citation database in science. For technical reasons, it only covered citations from certain journals and years, creating quasi-random variation: some citations became visible, while others remained invisible. We identify the effects of citation metrics by comparing the predictiveness of visible to invisible citations. Citation metrics increased assortative matching between scientists and departments by reducing information frictions over geographic and intellectual distance. Highly cited scientists from lower-ranked departments ("hidden stars") and from minorities benefited more. Citation metrics also affected promotions and NSF grants, suggesting Matthew effects. (*JEL* A14, I23, J44)

The allocation of talent to productive positions in society is of utmost importance for the creation of new ideas, technological progress, and economic growth (e.g., Murphy, Shleifer, and Vishny 1991; Jones 1995a; Weitzman 1998; Romer 1986, 1990; Hsieh et al. 2019). As talent is scarce, private sector firms and universities increasingly rely on performance metrics to identify talented individuals (e.g., Hoffman, Kahn, and Li 2018; Bersin 2013). In academia, performance metrics based on citations and publications affect hiring, promotions, wages, research funding, and the prestige of academics (e.g., Hamermesh and Schmidt 2003; Ellison 2013). Due to their increasing use, concerns have been raised about a potential overreliance on performance metrics in science (DORA 2013; CoARA 2022). Despite

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the importance of such metrics, as well as the recent discussions, there is virtually no evidence that quantifies how performance metrics affect the organization of science.

In this article, we provide the first systematic evidence of the impact of performance metrics on the allocation of talent and on scientific careers. Specifically, we study how citation metrics affect the assortative matching between scientists and universities, which groups benefit most from citation metrics, and how citation metrics affect career outcomes, such as promotions and research funding.

Our empirical strategy exploits the introduction of the *Science Citation Index* (SCI), which led to quasi-random variation in the visibility of individual scientists' citation counts. While researchers always had a rough sense of the influence of scientific work, it was impossible to systematically measure citations until the 1960s. This changed fundamentally in 1963 when Eugene Garfield published the first *Science Citation Index*. For the first time, it became possible to identify the highest-cited papers and researchers. The Nobel laureate and molecular biologist Joshua Lederberg lauded the invention of the SCI with the words "I think you're making history, Gene!" (Wouters 2017, p. 492). Scientists, funding bodies, and university administrators immediately started to use citation counts in hiring, promotion, and funding decisions. The sociologist Harriet Zuckerman remarked in the *New York Times* that there are "cases of people who have been asked to go count their own citations, and also of deans and administrations who have asked for citation counts" (Charlton 1981).

In the first part of the article, we investigate how the availability of citation metrics affects the assortative matching between scientists and departments. We document that the correlation between scientists' citation counts and the rank of their department increased by 61 percent. At the same time, scientists' publication counts became 46 percent less predictive of their department rank. These changes over time suggest that hiring committees started to attach more weight to citation counts and less weight to other observable characteristics such as publications when evaluating candidates. The increased correlation between scientists' citations and the ranking of their departments may be spurious for various reasons. For example, the increasing importance of expensive research labs and of federal research funding (e.g., Kantor and Whalley 2022) could disproportionately favor leading departments and allow them to attract star scientists, who turn out to be highly cited. Similarly, increases in team production (e.g., Wuchty, Jones, and Uzzi 2007; Jones 2009) may have spurred collaborations within departments and, hence, made department quality more critical for citations of individual scientists.

We estimate the causal effect of citation metrics by exploiting that, for technical reasons, the SCI only covered citations in a subset of years and journals. Only these citations became *visible* to the scientific community. In contrast, other citations remained *invisible* to contemporaries, yet are observable in modern citation data. The variation in the visibility of citations stems from two sources: variation in the coverage of citations (i) over time and (ii) across journals. First, citations appearing in *citing* articles until 1960 were invisible. With the first edition of the SCI, citations from citing articles in 1961 became visible. Due to technical constraints, the coverage of the SCI was interrupted for two years. Hence, citations appearing in citing articles in 1962 and 1963 remained invisible at the time. After 1964, the SCI was published yearly, and thus, citations appearing in citing articles after 1964 became visible. Second, due to a lack of computing power, the SCI only covered citations in certain journals. As a result, some citations appearing in covered years (1961 and from 1964 onward) remained invisible if they came from citing articles published in journals not indexed by the SCI. Crucially, in the early years, the selection of citing journals was somewhat arbitrary because the lack of citation data meant that journal rankings did not exist.[1]

Importantly, our empirical strategy exploits when and where a scientist's papers were *cited*, not when and where they were published. The *cited* papers could be published in any journal and in any earlier year. The following example of two hypothetical scientists illustrates our identification strategy: suppose that both scientists published a paper in 1957 (in any journal). One of the papers was cited in *Nature* in 1961, while the other one was cited in *Nature* in 1962. As the SCI covered citations in 1961 but not in 1962, the first citation became visible to contemporaries, while the second remained invisible. Using modern citation data, we can, however, observe both visible and invisible citations.

For our analysis, we combine new data on historical faculty rosters of US universities from the *World of Academia Database* (Iaria, Schwarz, and Waldinger 2022) with extensive publication and citation data from *Clarivate Web of Science*. These data enable us to construct the most comprehensive individual and department rankings for the 1960s. In addition, we digitize lists from historical volumes of the SCI, which specify the exact citing journals that were indexed in each volume of the SCI. This allows us to measure which citations were visible and, thus, to reconstruct the information set available to scientists in the 1960s.

We estimate the effect of citation metrics on the match between scientists and departments by comparing the relative importance of visible to invisible citations. We find that visible citations are four times as predictive of scientists' department rank than invisible citations. Specifically, scientists with a 10 percentile higher visible citation count were, on average, placed at a 2.5 percentiles higher ranked department in 1969. For instance, a mathematician would be placed at Princeton or Chicago as opposed to Columbia or Brandeis. In contrast, scientists with a 10 percentile higher invisible citation count were on average only placed at a 0.6 percentiles higher ranked department. This pattern holds even if we control for detailed publication records, that is, for the number of publications in each journal (e.g., two *Nature*, one *Science*, and one *PNAS* publication) and in each year (e.g., one publication in 1956, two in 1960, and one in 1964). Note that it is not surprising that even invisible citations affect the matching between scientists and departments since the academic community always had some knowledge of the quality of scientists' research, even if precise citation counts were not available.

Despite the somewhat arbitrary nature of the SCI coverage, two main concerns could potentially invalidate this identification strategy. First, visible citations may come from articles in higher-quality journals. Second, as the SCI was introduced in 1961, visible citations occur in later years, on average, and may have a larger impact on career outcomes in 1969. As a consequence, the impact of visible citations on scientists' careers would be overestimated.

[1] In fact, the impact factor, which nowadays is used to rank academic journals, was invented by the creators of the SCI (Garfield 1979, p. 150).

To address the quality concern, we compute measures of the quality of citing journals. We find that visible and invisible citations come from journals of similar quality. We also provide further evidence that differences in the quality of citing journals do not bias our results. For this test, we estimate regressions that only consider citations from the set of citing journals that were indexed in the first edition of the SCI. This analysis compares scientists whose paper was cited, for example, in *Science* in 1961, and was therefore visible, to scientists whose paper was cited in *Science* in 1963, and was therefore invisible.

To address the timing concern, we confirm that the results hold in specifications that exclusively rely on across-journal variation in the visibility of citations. This analysis compares scientists whose paper was cited in the same year (e.g., 1961) but one citation occurred in the *Journal of the American Chemical Society*, and was thus visible in the SCI, while the other citation occurred in *Chemical Reviews*, and was thus invisible.

The quality of citing journals and the timing of citations could interact to make visible citations more predictive for assortative matching. To address this concern, we introduce an additional specification. For this test, we partition the citation space into four mutually exclusive sets depending on where and when a scientist was cited: (i) *visible citations*: citations from journals that were indexed in the SCI in years when the SCI was published; (ii) *pseudovisible citations*: citations from journals that were indexed in the SCI in 1961 but from years when the SCI was not published; (iii) *invisible citations* (*SCI years*): citations from journals that were not indexed in the SCI in years when the SCI was published; and (iv) *invisible citations* (*non-SCI years*): citations from journals that were not indexed in the SCI in 1961 and from years when the SCI was not published.

We find that the coefficient on visible citations is almost identical to the coefficient in the baseline specification. Moreover, the coefficient on pseudovisible citations is considerably smaller and very similar to the two coefficients on invisible citations in SCI years and in non-SCI years. This indicates that citations in journals that were indexed by the SCI only had a differential impact in years in which the SCI was actually available. These results support the validity of our identification strategy.

Next, we shed light on two potential mechanisms that could underlie the increase in assortative matching based on citation metrics. First, scientists with few citations may have disproportionately left academia. We find that scientists with a 10 percentile higher visible citation count were 3.4 percentage points (or 5.0 percent) less likely to leave academia between 1956 and 1969. In contrast, invisible citations did not affect the probability of leaving academia. Second, highly cited scientists may have moved to higher-ranked departments. We show that scientists with a 10 percentile higher visible citation count were 0.8 percentage points (or 17.5 percent) more likely to move to a higher-ranked department between 1956 and 1969. Invisible citations had no effect on moving to a higher-ranked department. Overall, these results indicate that both mechanisms increased assortative matching.

Citation metrics may matter more in situations where peers did not have good information on the quality of a potential hire. We, therefore, explore whether citation metrics reduced information frictions across geographic and intellectual distance.

We find that citation metrics only impacted moves to higher-ranked departments that were geographically far but not to departments that were geographically close. Similarly, we find that citation metrics only impacted moves to higher-ranked departments where the moving scientist had not been cited before the move. These results suggest that citation metrics helped overcome information frictions. Reducing these frictions may have enabled departments to discover scientists in lower-ranked departments, even if they had not interacted before.

In the second part of the article, we investigate the heterogeneous effects of citation metrics. First, we show that scientists in higher percentiles of the individual-level citation distribution, and especially those above the ninetieth percentile, benefited disproportionately from the availability of citation metrics. Second, we find that the availability of citation metrics particularly benefited highly cited academics who were originally placed in lower-ranked departments. Thus, citation metrics enabled the discovery of these "hidden stars." This suggests that the introduction of the SCI helped to overcome misallocation by helping the highest-cited scientists move to higher-ranked departments. We also investigate the characteristics of these hidden stars. We provide evidence that these scientists, on average, obtained their PhD from worse universities and that they were more likely to be female. Third, we investigate whether minority scientists (female, Jewish, Hispanic, or Asian) differentially benefited from the introduction of the SCI. While we do not find evidence that minority scientists, on average, benefited more from citation metrics than majority scientists, we find evidence that among star scientists, minority scientists benefited slightly more. Overall, these results suggest that the availability of more "objective" performance metrics helped highly cited scientists in lower-ranked departments and highly cited scientists from minority groups.

In the last part of the article, we study the impact of citation metrics on other career outcomes: promotions and receiving research grants. In particular, we analyze whether scientists who were assistant or associate professors in 1956 were promoted to full professors by 1969. The probability of promotion increased by 4.1 percentage points (or 5.8 percent) for scientists with a 10 percentile higher visible citation rank. In contrast, invisible citations did not affect promotions. Similarly, we find that scientists with a 10 percentile higher visible citation rank were 19.0 percent more likely to receive a National Science Foundation (NSF) grant. These results indicate that citation metrics not only affected assortative matching but also had direct impacts on the careers of scientists and changed the allocation of resources. Scientists with many visible citations accrued additional rewards and recognition, suggesting the presence of Matthew effects (Merton 1968).

This paper contributes to three different strands of the literature. First, our paper contributes to the body of literature on the economics of science and the creation of knowledge. The existing literature has shown that scientists have to process increasing amounts of knowledge to advance the scientific frontier (Jones 2009) and that access to the knowledge frontier is crucial for producing science (Iaria, Schwarz, and Waldinger 2018). Additional contributions have studied the importance of superstar scientists (Azoulay, Graff Zivin, and Wang 2010), peer effects and scientific productivity (e.g., Waldinger 2010, 2012; Borjas and Doran 2012), and the role of editors (e.g., Card and DellaVigna 2020). More recently, increased attention has been paid to inefficiencies in the scientific process, such as the Matthew effect (Azoulay, Stuart, and Wang 2014; Jin et al. 2019), gatekeepers (Azoulay, Fons-Rosen, and Zivin 2019), or discrimination (e.g., Card et al. 2020, 2022; Iaria, Schwarz, and Waldinger 2022; Koffi 2021; Hengel 2022).

Despite all these papers making use of publication and citation data, and a long-standing sociological debate on this fundamental aspect of modern science (e.g., Lotka 1926; Merton 1968; Zuckerman and Merton 1971; Wouters 1999a, 2014; Muller and Peres 2019; Biagioli and Lippman 2020; Pardo-Guerra 2022), there is no causal evidence on how performance metrics affect scientific careers.[2] Our paper is the first to provide causal evidence that citation metrics fundamentally impact the organization of science.

Second, our findings contribute to the literature on performance metrics in the labor market. As highlighted by the theoretical models of Holmstrom and Milgrom (1991) and Feltham and Xie (1994), the use of performance metrics shapes incentives of agents in the labor market. The key empirical challenge to estimating the impact of performance metrics is that, in most cases, it is impossible to measure performance before the introduction of a specific performance metric. As a result, researchers often lack a valid counterfactual. This makes empirical evidence on how performance metrics affect the allocation of talent exceedingly rare. A few notable exceptions study the effect of performance metrics in the teacher labor market (Rockoff et al. 2012) and on first placements of MBA graduates (Floyd, Tomar, and Lee 2022). The unique advantage of our setting is that we observe the information set available at the time and, importantly, what was not part of that information set.[3]

Last, we contribute to research on assortative matching in labor markets (e.g., Abowd, Kramarz, and Margolis 1999; Andrews et al. 2008; Card, Heining, and Kline 2013; Song et al. 2019). We show that performance metrics can increase assortative matching by lowering information frictions.

I. The Science Citation Index: Background and Data

A. *The Creation of the Science Citation Index*

The SCI was the first systematic international and interdisciplinary citation index. During the 1950s, Eugene Garfield and his newly founded Institute for Scientific Information (ISI) developed the technology to construct a citation index. By the early 1960s, this endeavor was supported by grants from the National Institutes of Health and the National Science Foundation. In November 1963, these efforts came to fruition, and the first edition of the SCI was published, covering citations in 1961 (Garfield 1963a; see online Appendix Figure A.1 for a picture of the first SCI). The

[2] Some papers document that citation metrics, such as the h-index or citation counts, are correlated with career outcomes (e.g., Ellison 2013; Jensen, Rouquier, and Croissant 2009; Hilmer, Ransom, and Hilmer 2015).

[3] Since we measure the information set of contemporaries in the 1960s, our analysis allows us to identify the effects of revealing new information on labor market outcomes. In this, we add to the literature on how information disclosure and new information technologies affect market efficiency (e.g., Jensen 2007; Koudijs 2015; Tadelis and Zettelmeyer 2015; Steinwender 2018; Bernstein, Frydman, and Hilt forthcoming).

ABELL MR	----------*50*	ARCH PATHOL---------		50	1
EMERY GN		CAN J BIOCH	61	39	977
	--------------50-	ARCH PATH-----------		50	23
HRSTKA V		ARCH I PHAR	61	130	304
	--------------56-	ARCH PATH-----------		61	360
WILLIAMS GE		J PATH BACT	61	82	281
	--------------57-	AMER J CLIN PATH----		28	272
INKLEY SR		ARCH IN MED	61	108	903
LAUFER A		PATH MICROB	61	24	72
	--------------61-	CANCER--------------		14	318
GOSLING JR		CANCER	61	14	330

Figure 1. Entry in the Science Citation Index

Notes: This figure shows a sample entry of the 1961 volume of the SCI. It lists five cited papers for "Abell MR." Murray R. Abell was Professor of Pathology (Medicine) at the University of Michigan. The cited papers could have been published in any year until 1961 (here, 1950 (twice), 1956, 1957, and 1961). The five papers are cited by six citing articles. Because this example is from the 1961 volume of the SCI, all citations are from 1961.

SCI quickly became the "most widely used and authoritative database of research publications and citations" (Birkle et al. 2020).[4]

To construct the SCI, Garfield and his team selected 613 *citing* journals from the physical and life sciences and collected all citations appearing in articles in these journals in 1961 (Garfield 1963b). This enabled them to identify all papers that were cited by these articles in 1961. The *cited* papers could have been published in any previous year (i.e., not only in 1961) and in any journal (i.e., not only in the set of citing journals but in any journal or book).

This information was stored on punch cards and converted to magnetic tapes, which were processed by IBM computers (Garfield 1963a, p. x [sic]). Entries were ordered by last names and initials of scientists (see online Appendix Figure A.1). Figure 1 shows the 1961 entry for the medical scientist Murray Abell. His entry covers five cited papers: a 1950 paper in *Archives of Pathology* (vol. 50, p. 1), another 1950 paper in *Archives of Pathology* (vol. 50, p. 23), a 1956 paper in *Archives of Pathology* (vol. 61, p. 360), a 1957 paper in the *American Journal of Clinical Pathology* (vol. 28, p. 272), and a 1961 paper in *Cancer* (vol. 14, p. 318). Each of these papers was cited at least once in 1961; e.g., the 1956 *Archives of Pathology* paper was cited by one article in 1961 in the *Journal of Pathology and Bacteriology* (vol. 82, p. 281). Overall, these five papers received six citations in 1961.

For technical reasons, the SCI did not collect citations for 1962 and 1963. As "[t]he 1961 SCI was the result of an experimental research program," its preparation took more than two years (Garfield 1965). After releasing the 1961 SCI in November 1963, the ISI moved on to preparing the 1964 SCI.[5] From then on, the SCI was published quarterly. The set of indexed citing journals quickly expanded from 613 in 1961 to 2,180 in 1969.

[4] The SCI was revolutionary because it created a novel metric of scientific productivity that individuals were unable to compile for themselves. No scientist would have had the capacity to count citations to their own work because it would have required sifting through hundreds of thousands of potentially citing articles. In contrast, earlier metrics of scientific productivity, such as publication catalogs, aggregated information that was already individually available (e.g.,, the *Catalogue of Scientific Papers* (Csiszar 2017)).

[5] The 1962 and 1963 SCIs were released only in 1972 (Garfield 1972). For this reason, we measure outcomes in 1969 and, hence, before the ISI had begun to fill in gaps in coverage.

The SCI was an immediate success. By the late 1960s, every major university had a subscription (Garfield 1972, p. 4). For example, in 1965 chemists at Ohio State University lobbied the library administration to subscribe to a second copy of the SCI, in addition to the copy that was already available in the medical library (see online Appendix Figure A.3).[6]

B. *Data*

Reconstructing SCI Coverage from the Web of Science.—For contemporaries, citations were only visible if they came from citing articles in journals that were indexed by the SCI. This means that only an incomplete set of citations was visible at the time. Citations before the SCI's introduction in 1961, as well as those from 1962 and 1963, and from journals that were not indexed by the SCI remained invisible. In the 1970s and 1980s, the SCI was expanded backward to cover additional years and journals and later became part of the *Web of Science*. As a result, the *Web of Science* covers both citations that were visible to contemporaries and citations that were invisible at the time but became available during the backward expansions.

We reconstruct the sets of citations that were visible and invisible to contemporaries. For this purpose, we hand collect yearly lists of citing journals from the printed historical SCI volumes. We digitize these lists and hand link them to the *Web of Science*. Online Appendix Figure A.2 shows a sample journal list. Using this linking procedure, we can identify which citations were part of the information set of the 1960s and which ones were not.

Faculty Rosters.—To study how the introduction of citation metrics affects the careers of academics, we use data containing faculty rosters for nearly all universities in the United States from the *World of Academia Database* (see Iaria, Schwarz, and Waldinger 2022). The data contain almost comprehensive cross sections of all US academics for the years 1956 and 1969. Because the SCI only counted citations for the natural and biomedical sciences, we focus on all academics who worked in either biology, biochemistry, chemistry, physics, mathematics, or medicine. For the period of our analysis, the database provides the most comprehensive data on academics in the United States (for further details, see Iaria, Schwarz, and Waldinger 2022). For the 1969 cross section, the data contain 27,315 scientists at 1,477 departments in 384 universities (panel B of Table 1).

The *World of Academia Database* has two unique advantages for our purpose. First, it enables us to identify the department (e.g., physics at Berkeley) of each academic. Second, it contains complete faculty rosters, which allows us to observe both academics who received citations and, importantly, academics who did not receive any citations. This enables us to construct comprehensive individual and department rankings based on *all* academics and not only based on those who published and were cited.

[6] By 1966, the SCI was not only available as printed volumes but could also be purchased on magnetic tapes. The magnetic tapes provided the raw data for constructing citation counts and for conducting quantitative citation analyses (Garfield 1966). Furthermore, the ISI published five-year cumulations of the SCI. For example, the 1965–1969 compilation included all citations between 1965 and 1969 (Garfield 1971).

Table 1—Descriptive Statistics

	Mean	SD	Min	Max
Panel A. Summary statistics				
Publications	8.75	16.65	0	405
Visible citations	46.99	128.05	0	3,346
Invisible citations	18.93	57.95	0	2,010
Full professor share	0.40	0.49		
Female share	0.10	0.30		
Panel B. Number of observations				
Citations				1,800,669
Publications				239,124
Scientists				27,315
Departments				1,477
Universities				384

Notes: Panel A reports summary statistics at the scientist level for the cross section of scientists observed in 1969. *Publications* are the number of papers a scientist published between 1956 and 1969, *visible citations* are the number of citations these papers received between 1956 and 1969 that were visible in the SCI, and *invisible citations* are the number of citations these papers received between 1956 and 1969 that were not visible in the SCI. Panel B reports the number of observations at the citation, publication, scientist, department, and university level.

Linking Scientists with Publications and Citations.—To count scientists' publications and citations, we link the *World of Academia Database* with publication and citation data from the *Web of Science*. We use the cascading linking algorithm developed in Iaria, Schwarz, and Waldinger (2022) (see online Appendix B.1.1 for details).

For the 1969 cohort of scientists, we link their publications and citations from 1956 to 1969. This enables us to measure the number of papers that each scientist published in this period and to count the citations that these papers received from the time they were published until 1969. Importantly, for our identification strategy, we observe the complete citation network and thus the exact journal in which a certain paper was cited. This allows us to measure whether the citations were covered in the SCI and were thus visible to contemporaries.

The average scientist in our data published 8.75 papers between 1956 and 1969 (panel A of Table 1). These papers received 47 citations that were visible to contemporaries and 19 citations that were invisible to contemporaries but can be observed today.[7] As has been documented by a large literature in the sociology of science, citations of academics are highly skewed (e.g., Lotka 1926). The most highly cited scientists in our data received more than 3,000 visible and more than 2,000 invisible citations between 1956 and 1969.

Constructing Scientist Rankings.—Using our scientist-publication-citation-linked data, we can construct rankings based on citations and publications. Within each

[7] We show below that the different distributions of visible and invisible citations do not drive our results.

subject, we rank scientists according to their citation (or publication) counts between 1956 and 1969. We then calculate each scientist's percentile rank in the subject-specific distribution of citations (or publications), assigning 100 to the best and 1 to the worst scientist. This variable transformation allows us to compare the scientists' relative positions in the citation distributions, even if these distributions differ across subjects. For example, the median biologist received 2 citations, while the median chemist received 9 citations. If percentiles cannot be uniquely assigned because too many scientists have the same number of citations or publications, we assign the midpoint of the corresponding percentiles.[8] This is particularly important for scientists with zero citations. Alternative assignments of percentile ranks to scientists with zero citations do not affect our findings (see online Appendix C.2.3).

Constructing Department Rankings.—Our data also enable us to construct the most comprehensive department rankings for this time period. These are the first rankings for this period that are based on scientific output, as opposed to reputational surveys. In addition, our rankings cover a much larger number of departments than previously available survey-based rankings. In fact, the practice of ranking departments by their research output only developed as a result of citation indexing.

We rank all 1,477 departments in 384 universities on the basis of the average total citations received by scientists in each department. As outlined above, the rankings avoid systematic error because the *World of Academia* database also lists all scientists who have not published and/or were not cited in our study period. In our main department ranking, we construct the leave-out mean of the number of citations received by scientists in a given department, that is, the average citation count of scientist i's colleagues. We then assign the percentile rank in the subject-specific distribution of leave-out mean citation counts, assigning 100 to the best and 1 to the worst department. We use the percentile rank because it allows us to compare the relative position of departments in different subjects (physics, chemistry, and so on), which have different numbers of departments, scientists, and average citations per scientist.

In robustness checks, we show that our findings are robust to using several alternative department rankings. First, we construct analogous department percentile ranks based on publications. Second, we construct department percentile ranks using reputation-based rankings from Roose and Andersen (1970) and Cartter (1966). As highlighted above, the reputation-based rankings cover far fewer universities.[9] In online Appendix B.2, we list the top 20 departments in each subject, as measured by the various rankings.

[8] For example, in physics 30.37 percent of observations have 0 citations. For the main results, we assign the midpoint between the first percentile and the thirty-first percentile, that is, a percentile rank of 15.5, to each of these observations.

[9] The Cartter ranking contains 106 universities, and the Roose-Andersen ranking contains 130, while our baseline ranking contains 384 universities. The alternative rankings strongly correlate with our main citation-based ranking. The correlation between the Cartter ranking and our citation-based ranking is 0.68, while the correlation between the Roose-Andersen ranking and our citation-based ranking is 0.70.

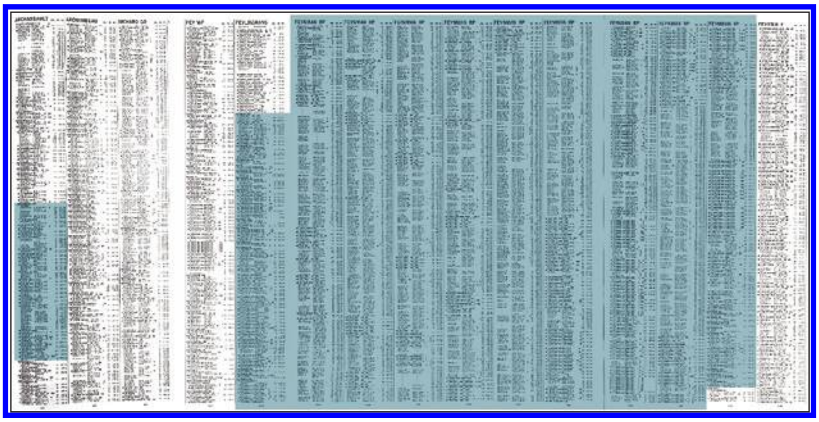

FIGURE 2. COMPARISON OF SCI ENTRIES

Note: This figure compares the entries in the 1965–1969 cumulation of the SCI (Garfield 1971) for two physicists at Caltech: Charles Archambeau on the left and Nobel laureate Richard Feynman on the right.

C. *How Was the SCI Used in Hiring and Promotions?*

While the SCI was predominantly designed to facilitate literature research, it was immediately used to evaluate scientists. For example, Eugene Garfield remembered, "The SCI's success did not stem from its primary function as a search engine, but from its use as an instrument for measuring scientific productivity" (Garfield 2007, p. 65).

The eminent biologist Richard Dawkins described the SCI as a publication that is "intended as an aid to tracking down the literature on a given topic. University appointments committees have picked up the habit of using it as a rough and ready (too rough and ready) way of comparing the scientific achievements of applicants for jobs" (Dawkins 2016, p. 427).

The SCI made scientists' citations visible and readily accessible for the first time. Because the SCI was organized by cited authors, it was easy to measure and compare the citation counts of scientists. Figure 2 shows one such comparison for two scientists working at Caltech. The box on the left shows citations of the physicist Charles Archambeau. The box on the right shows the citations of the 1965 physics Nobel laureate Richard Feynman. As one contemporary remarked, "[a]n early form of research evaluation of individuals made use of a ruler to measure column inches of citations!" (Birkle et al. 2020, p. 364).

Very quickly, scientists, funding bodies, and university administrators started to use citation counts in hiring, promotion, and funding decisions. Some universities even made citations a mandatory metric in the evaluation of applicants' portfolios (Wade 1975, p. 429). The importance of newly available citation metrics is exemplified in the court case *Johnson v. University of Pittsburgh*.[10] In 1973, Sharon

[10] *Johnson v. University of Pittsburgh*, W.Da. PA., 1977.

Johnson sued the biochemistry department at the University of Pittsburgh for sex discrimination. Her legal case argued that she was overlooked for tenure even though her papers had received more citations (as measured in the SCI) than those of two recently tenured male colleagues.

The SCI's Impact on Assortative Matching: Suggestive Evidence.—We first provide suggestive evidence of the impact of the citation metrics on the assortative matching of academics and departments. If departments began to use the SCI to evaluate scientists, we would expect that the correlation between a scientist's citations and their department rank increased after the introduction of the SCI. We find that the correlation between a scientist's individual citation rank and their department rank increased by 61 percent between 1956 and 1969 (panels A and B of Figure 3). In contrast, the correlation between the individual publication rank and the department rank decreased by 46 percent (panels C and D of Figure 3).

This evidence is in line with the hypothesis that the introduction of citation metrics increased the reliance of hiring decisions on citations and decreased the reliance on other observable characteristics such as publications. However, the increasing correlation between scientists' citation rank and their department rank may have been caused by other factors. For example, the increasing importance of expensive research labs or federal research funding (e.g., Kantor and Whalley 2022) could have disproportionately favored leading departments and allowed them to attract highly cited scientists. Similarly, increases in team production (e.g., Wuchty, Jones, and Uzzi 2007; Jones 2009) may have spurred within-department collaborations and, hence, may have made department quality more important for scientists' citations. To overcome these challenges, we introduce a novel identification strategy that allows us to isolate the causal effect of citation metrics on assortative matching in academia.

II. The Effect of Citation Metrics on Assortative Matching

A. *Empirical Strategy*

We identify the causal effect of citation metrics by comparing the effect of citations that were *visible* in the SCI to the effect of citations that remained *invisible*. For technical reasons, the SCI only covered citations from citing articles in a subset of journals and years. Hence, only citations from citing articles in this subset were visible to the scientific community. In contrast, other citations remained invisible because they were not covered in the SCI. Importantly, the cited papers could have been published in any journal and in any previous year. Therefore, scientists' visible citation counts were not determined by the journals in which their papers were published but only by the journals in which their papers were cited.

As described above, the first volume of the SCI covered citations from 1961 in any of the 613 citing journals. As a result, all 1961 citations in those 613 journals became visible in the SCI, while citations before 1961 and in other journals remained invisible. Due to limited computing power, the collection of citation data was interrupted in 1962 and 1963. By 1964, data collection resumed. The set of indexed citing journals quickly expanded from 613 in 1961 to 2,180 in 1969. As a

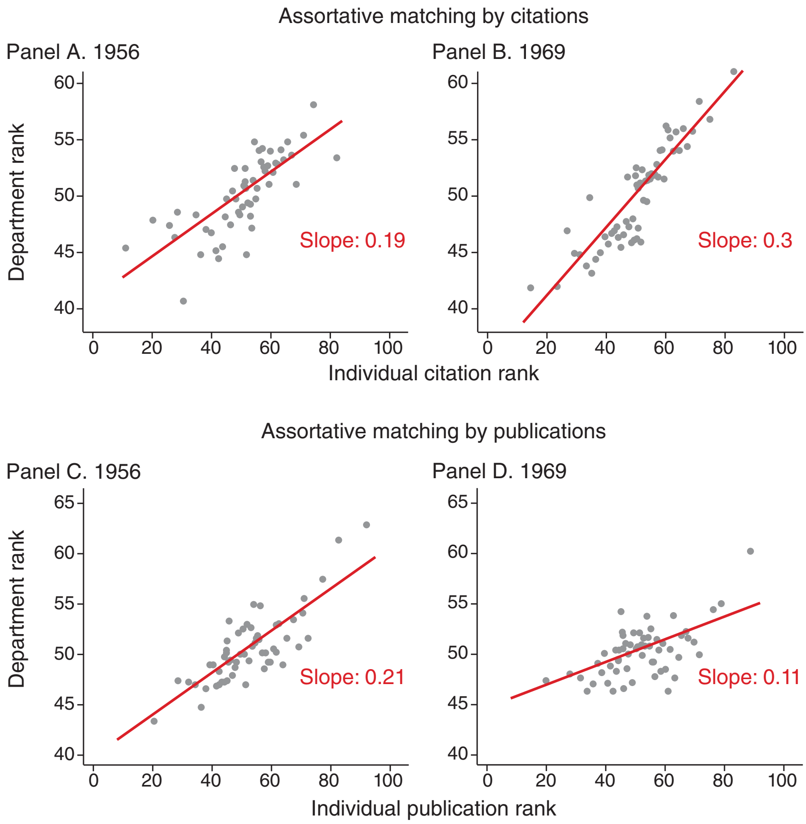

Figure 3. Assortative Matching before and after Citation Metrics

Notes: Panels A and B show the correlation of scientists' citation rank and their department rank for two cross sections: 1956 and 1969. Panel A shows a binned scatterplot for 1956 and, thus, before the introduction of the SCI. While we can now measure these citations, they were not observable at the time. Panel B shows a binned scatterplot for 1969 and, thus, after the introduction of the SCI. The regression coefficient in both panels is conditional on an individual's publication rank. The *p*-value of the test that the slope coefficients in panels A and B are equal is 0.008. Panels C and D show the correlation between scientists' publication rank and their department rank. Publications were observable to contemporaries in both 1956 and 1969. The regression coefficient in both panels is conditional on an individual's citation rank. The *p*-value of the test that the slope coefficients in panels C and D are equal is 0.007.

result, the visibility of citations was affected by two sources of variation: first, in which *year* a paper was cited and second, in which *journal* it was cited.[11]

Our data enable us to reconstruct which citations were part of the information set of the 1960s; that is, we measure citations that were *visible* in the SCI. Crucially, we can also reconstruct which citations were not part of that information set, that is, citations that were *invisible*. Invisible citations can be measured today because citation databases were expanded to include citations for additional years and for a larger set of citing journals.

[11] Below, we provide evidence that the quality of citing journals or differences in the timing of citations do not drive our findings.

TABLE 2—IDENTIFYING VARIATION FOR SPECIFICATION 1

	Citations in Journal A	Citations in Journal B	Citations in Journal C
1956			
1957		1	
1958			
1959	1		1
1960			
1961	1	1	
1962			1
1963	1		
1964			
1965		1	
1966		3	
1967	2		
1968			
1969			1

Notes: This table reports citations of a hypothetical scientist's papers. Numbers in dark blue cells show citations that were visible in the SCI because the citation occurred in a journal and year (1961 or 1964–1969) that was covered by the SCI. Numbers in light blue cells show citations that were invisible in the SCI but are observable today.

Table 2 illustrates the identifying variation for a hypothetical scientist. It reports citations to the scientist's papers, which were published in any journal and in any year. These papers were cited in articles from journals A, B, and C between 1956 and 1969. Journal A was in the initial set of 613 citing journals indexed by the SCI in 1961. Journal B was added to the SCI in 1966, whereas journal C was not indexed in the 1960s. The dark blue cells indicate citations that were visible to contemporaries because the SCI collected citations for these years and citing journals. The light blue cells indicate citations that were invisible because the SCI did not collect data for these years and citing journals. In other words, citations in dark blue cells were part of contemporaries' information set, while citations in light blue cells were not.

In the example, the hypothetical scientist's papers were cited in articles published in journal A in 1959, in 1961, in 1963, and twice in 1967. The citations in 1959 and 1963 were invisible because the SCI did not exist for those years. In contrast, the citations in 1961 and 1967 were visible in the SCI. Similarly, the scientist's papers were cited in articles in journal B in 1957, 1961, 1965, and three times in 1966. Because journal B was added to the SCI only in 1966, the citations in 1957, 1961, and 1964 were invisible. In contrast, the three citations in 1966 were visible. Finally, the scientist's papers were cited in articles in journal C in 1959, 1961, and 1969. As journal C was not indexed in our study period, all of these citations were invisible to contemporaries.

Hence, if contemporaries had looked up the scientist's total citations in the SCI in 1969, they would have observed six citations; that is, the scientist had six *visible* citations. In addition, the scientist had eight citations that were *invisible* at the time.

Using modern citation data, we can observe both visible and invisible citations. For each scientist *i*, we separately count the number of visible and invisible citations between 1956 and 1969 to *i*'s papers published between 1956 and 1969.

B. *Specification 1: Visible versus Invisible Citations*

Our identification strategy exploits the differential visibility of scientists' citations. If the very measurement of citations affects the assortativeness of the match between academics and universities, visible citations should be more predictive of career outcomes than invisible ones. The identifying assumption underlying this new empirical strategy is that the effect of visible and invisible citations would be the same if both had been covered in the SCI. Given the arbitrary timing of the introduction of the SCI and the lack of coverage for the years 1962 and 1963, this seems plausible. Nonetheless, there may be concerns that any effect might be driven by differences in the quality of the citing journals or the timing of citations, that is, by the two sources of variation in the visibility of citations. We address these concerns with alternative specifications outlined below.

We estimate the following regression:

$$(1) \qquad Dep.\ Rank_i = \delta \cdot Visible\ Citations_i + \theta \cdot Invisible\ Citations_i + \pi \cdot Publications_i + Subject\ FE + \epsilon_i,$$

where $Dep.\ Rank_i$ is the department rank of scientist *i* in 1969, where 100 is the best and 1 the worst department.[12] $Visible\ Citations_i$ measure scientist *i*'s visible citations. $Invisible\ Citations_i$ measure scientist *i*'s invisible citations. In the baseline specification, we measure citations as the percentiles in the distributions of visible and invisible citations.[13] $Publications_i$ flexibly control for scientist *i*'s publications. *Subject FE* control for differences between academic subjects. To account for potential correlations of regression residuals in a certain department, e.g., in chemistry at Berkeley, we cluster all standard errors at the department level.

To study how citation metrics affect assortative matching, we compare the magnitudes of the estimated coefficients $\hat{\delta}$ and $\hat{\theta}$. If the visibility of citations in the SCI increased the assortativeness of the match between scientists and departments, we would expect that $\delta > \theta$. For example, the difference between δ and θ captures whether citations that occurred in 1961 instead of 1962 had a larger impact on the match between scientists and departments. Note that we would not expect θ to be zero because, even in the absence of the SCI, scientists will have an approximate idea about the importance and quality of other scientists' papers.

[12] In the main specification, we use the department ranking based on the leave-out mean of citations. All results are robust to using different measures of the department rank, e.g., based on citations, publications, or alternative department rankings based on contemporaneous reputation-based surveys (online Appendix Tables C.1 and C.2).

[13] We explore alternative transformations of citation counts in online Appendix Table C.3, e.g., standardizing citation counts or using the inverse hyperbolic sine of citations.

Table 3—Citations and Assortative Matching

	Dependent variable: *Department rank*				
	(1)	(2)	(3)	(4)	(5)
Panel A. Specification 1: Visible versus invisible citations					
Visible citations	0.299	0.320	0.280	0.247	0.237
	(0.034)	(0.031)	(0.035)	(0.035)	(0.035)
Invisible citations	0.103	0.068	0.062	0.061	0.060
	(0.023)	(0.020)	(0.021)	(0.023)	(0.024)
p-value (Visible = Invisible)	<0.001	<0.001	<0.001	<0.001	<0.001
R^2	0.138	0.140	0.153	0.232	0.261
Panel B. Specification 2: Visible versus pseudovisible versus invisible citations					
Visible citations	0.305	0.327	0.284	0.252	0.243
	(0.035)	(0.032)	(0.036)	(0.035)	(0.036)
Pseudovisible citations	0.033	0.012	0.013	0.028	0.022
	(0.021)	(0.020)	(0.020)	(0.022)	(0.023)
Invisible citations (SCI years)	0.030	0.029	0.030	0.020	0.023
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Invisible citations (non-SCI years)	0.057	0.044	0.037	0.025	0.029
	(0.017)	(0.016)	(0.016)	(0.016)	(0.017)
p-value (Visible = Pseudovisible)	<0.001	<0.001	<0.001	<0.001	<0.001
p-value (Visible = Invisible (SCI years))	<0.001	<0.001	<0.001	<0.001	<0.001
p-value (Visible = Invisible (non-SCI years))	<0.001	<0.001	<0.001	<0.001	<0.001
p-value (Pseudovisible = Invisible (SCI) = Invisible (non-SCI))	0.451	0.551	0.676	0.941	0.956
R^2	0.138	0.141	0.154	0.232	0.261
Subject fixed effects	Yes	Yes	Yes	Yes	Yes
Publications by year		Yes			
Publications by year × subject			Yes	Yes	Yes
Publications by journal				Yes	
Publications by journal × subject					Yes
Observations	27,315	27,315	27,315	27,315	27,315
Dependent variable mean	50.40	50.40	50.40	50.40	50.40

Notes: The table reports the estimates of equation (1) in the first panel and of equation (2) in the second panel. The dependent variable is the *department rank* in 1969, based on the leave-out mean of citations in the department of scientist *i*. The explanatory variable *Visible citations* measures scientist *i*'s individual rank in the distribution of visible citations. *Invisible citations* measures scientist *i*'s individual rank in the distribution of invisible citations. *Pseudovisible citations* measures scientist *i*'s individual rank in the distribution of pseudovisible citations (citations in journals indexed in the SCI in 1961 but for years not covered in the SCI, i.e., 1956–1960 and 1962–1963). *Invisible citations* (*SCI years*) measures scientist *i*'s individual rank in the distribution of invisible citations in SCI years (1961 and 1964–1969). *Invisible citations* (*non-SCI years*) measures scientist *i*'s individual rank in the distribution of invisible citations in non-SCI years (citations in journals not indexed in the SCI in 1961 and in years that were not covered, i.e., 1956–1960 and 1962–1963). We transform ranks into percentiles, where 100 is the best and 1 the worst department/scientist. *Publications by year* separately measures the number of scientist *i*'s publications in each year between 1956 and 1969. *Publications by journal* separately measures the number of scientist *i*'s publications in each journal (e.g., *Nature*). Standard errors are clustered at the department level.

We report estimates of equation (1) in panel A of Table 3. In column 1, we report a specification that controls for subject fixed effects. The coefficient for visible citations is around three times larger than the coefficient for invisible citations. Scientists with a 10 percentiles higher visible citation count were, on average, placed at a 3.0 percentiles higher ranked department in 1969. For example, a chemist would be placed at Harvard or Stanford as opposed to Northwestern University or the University of Southern California. In contrast, scientists with a 10 percentiles higher invisible citation count were, on average, only placed at a 1.0 percentiles higher ranked department.[14] We also report the *p*-value of a two-sided *t*-test for the equality of the two citation coefficients. We reject the equality of the two coefficients at the 0.1 percent level.

To rule out that these differences could potentially be explained by scientists' publication records, we include fine-grained controls for publications in columns 2–5 of Table 3. In column 2, we show that the results are robust to controlling for the number of publications by year, that is, controlling separately for the number of publications in 1956, 1957, and so on.[15] One might be concerned that differences in publication and citation patterns across the sciences could explain our findings. For example, mathematicians publish fewer papers and receive fewer citations than chemists or medical researchers. To address this concern, we show that the results are robust to separately controlling for the number of publications by year and subject (column 3).

Naturally, not only the number of publications but also the journal in which a paper was published may be correlated with citation counts and thus might bias our estimates. To overcome this challenge, we additionally control for the number of publications in each individual journal. That is, we add a variable that counts the number of papers in *Science*, another variable that counts the number of papers in *Nature*, and so on. In total, we add 1,745 variables that control for the number of publications in each journal (column 4). We also allow the effect of these controls to differ by subject, so that a publication in *Science* may have a different effect on the career of a physicist than on the career of a chemist (column 5). The results are robust to the inclusion of these fine-grained controls for scientists' publication records. In fact, the difference in the impact of visible and invisible citations increases with the inclusion of additional controls. With all controls (column 5), visible citations have a four times larger effect on the department rank than invisible citations. Online Appendix Figure C.1 illustrates these results graphically.

We show that these findings are robust to using alternative ways of ranking departments (online Appendix C.2.1), to using alternative transformations of individual citation counts (online Appendix C.2.2 and C.2.3), and to imposing additional sample restrictions (online Appendix C.2.4).

Alternative Explanation 1: Quality of Citing Journals.—Despite the somewhat arbitrary nature of the SCI coverage, the results would be biased if the visibility of citations in the SCI were correlated with other characteristics that impacted a scientist's department rank in 1969.

The first concern is that visible citations may come from citing articles in higher-quality journals (e.g., *Nature* or *Science*) and therefore have a larger impact on a scientist's career. It is important to note that this concern is somewhat mitigated

[14] As discussed above, it is not surprising that invisible citations are positively correlated with the department rank because they proxy for wider recognition by the scientific community.

[15] Since the number of scientists' publications takes many fewer values than the number of citations (see Table 1), especially when measuring publications separately by years (columns 2–5 in Table 3) and journals (columns 4–5 in Table 3), we do not use the percentile rank transformation of publications.

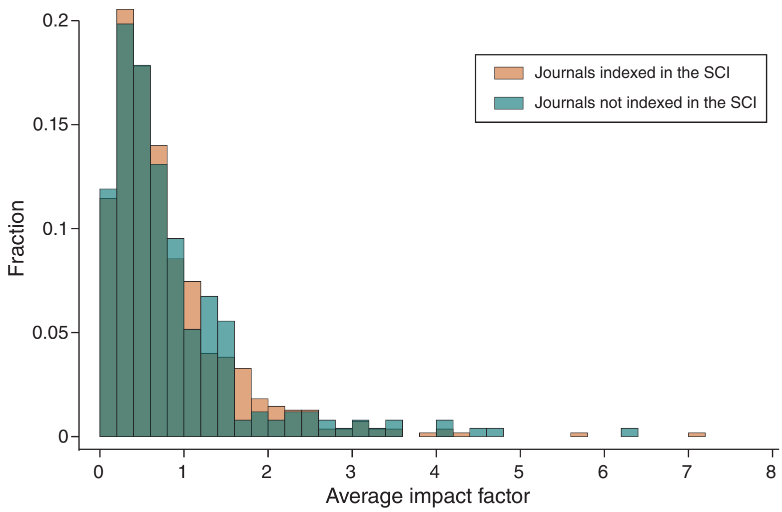

FIGURE 4. QUALITY OF JOURNALS INDEXED AND NOT INDEXED IN THE SCI

Notes: The figure shows histograms of impact factors for two sets of journals: journals indexed in the SCI in 1961 (orange) and journals not indexed in the SCI in 1961 (blue). For each journal, we average the impact factors over the pre-period (1956–1963).

because it was difficult to assess journal quality before the introduction of the SCI. Some of the citing journals initially indexed in the SCI turned out to be of relatively lower quality. Similarly, many journals that were, in fact, of high quality were not indexed during the first years of the SCI.

While it was not possible to quantitatively measure journal quality at the time, we can retrospectively compute measures of the quality of the citing journal and thereby assess whether visible citations came from better journals. For this test, we compute the impact factors for all citing journals in the pre-SCI period.[16] Journals that were indexed in the 1961 SCI had an average impact factor of 0.83, while journals that were not indexed had an average impact factor of 0.86 (p-value of test of equal means: 0.618). We also plot the distributions of the average impact factors for both types of journal in Figure 4. This analysis indicates that journals indexed in the 1961 volume of the SCI were not of higher quality than journals that were not indexed.

To provide additional evidence that differences in the quality of citing journals are not driving the results, we estimate regressions that only consider citations from a fixed set of journals. For this test, we only rely on variation over time in the visibility of citations. This allows us to abstract from potential differences in journal quality. In particular, we estimate regressions that only use visible and invisible citations

[16] Because the 1961 volume of the SCI was published in November 1963, we define the pre-SCI period as 1956–1963. The impact factor is calculated as the average number of citations in year t to articles published in that journal in the years $t-1$ and $t-2$.

from the set of journals that were included in the first edition of the SCI in 1961 (i.e., only using variation over time in citations from type A journals in Table 2).[17]

For example, the test compares scientists who were cited in *Nature* in 1961, and therefore these citations were visible in the SCI, to scientists who were cited in *Nature* in 1962, and therefore these citations were invisible. The hypothetical scientist presented in Table 2 would have three visible citations, one in 1961 and two in 1967, and two invisible citations, one in 1959 and one in 1963. For this test, we do not consider citations in type B or type C journals, that is, journals not indexed in the first SCI in 1961. The results that use only citations from type A citing journals are almost identical to the main results (see online Appendix Table C.6), indicating that differences in the quality of citing journals do not drive our findings.

Alternative Explanation 2: Timing of Citations.—The second concern stems from the differential timing of visible and invisible citations. As the SCI was introduced in 1961, visible citations, on average, occurred in later years than invisible ones. If more recent citations had more predictive power for career outcomes in 1969, the larger effect of visible citations may be spurious.

We address this concern by fixing the timing of citations and exclusively relying on across-journal variation in visibility. In particular, we estimate regressions that only use visible and invisible citations from years in which the SCI was available (i.e., 1961 and 1964–1969). This exercise compares scientists with the same publication record who were cited in similar years but in different journals, only some of which were covered in the SCI.[18]

For our hypothetical scientist presented in Table 2, this test considers six visible citations: one from journal A in 1961, two from journal A in 1967, and three from journal B in 1966. It also considers three invisible citations: one each from journal B in 1961 and 1965 and one from journal C in 1969.[19]

The results that use only citations from years in which the SCI was published are very similar to the main results (online Appendix Table C.7). The point estimates are almost identical, and the *p*-values for the difference in coefficients remain below the 0.1 percent level. These results strongly suggest that the differential timing of visible and invisible citations does not drive our findings.[20]

C. *Specification 2: Visible versus Pseudovisible versus Invisible Citations*

The quality of citing journals and the timing of citations might interact to make visible citations more predictive for assortative matching. To address such concerns, we introduce a second specification, which includes a placebo test that compares the predictiveness of different types of invisible citations. For this specification, we

[17] We visualize the underlying variation of this robustness check in panel B of online Appendix Figure C.2.

[18] As outlined above, in the early years, limited funding and computing power prevented the Institute for Scientific Information from covering a large number of journals in the SCI (Garfield 1963a, p. xvii). As a result, citations in many reputable journals remained invisible.

[19] See also panel C of online Appendix Figure C.2.

[20] As more journals were indexed in later years, even in this test, visible citations may, on average, come from later years. We address this concern by restricting the years for which we measure visible and invisible citations to even smaller windows (see online Appendix Table C.8).

Table 4—Identifying Variation for Specification 2

	Citations in Journal A	Citations in Journal B	Citations in Journal C
1956			
1957		1	
1958			
1959	1		1
1960			
1961	1	1	
1962			1
1963	1		
1964			
1965		1	
1966		3	
1967	2		
1968			
1969			1

Notes: This table reports citations to a hypothetical scientist's papers. We partition the citation space along two dimensions: (i) years covered by the SCI (blue) or not (red) and (ii) journals covered by the SCI (dark) or not (light). Dark blue cells show citations that were visible in the SCI. Dark red cells show pseudovisible citations, that is, citations that were invisible (because they came from years not covered by the SCI) but would have been visible had the SCI been published for those years. Light blue cells show invisible citations for years in which the SCI was published, that is, citations that came from journals not covered by the SCI in years when the SCI was published. Light red cells show invisible citations for years in which the SCI was not published, that is, citations that came from journals not covered by the SCI in years when the SCI was not published.

partition the citation space into four mutually exclusive sets depending on where and when a scientist was cited (see Table 4):

(i) *Visible citations*: citations from journals that were indexed in the SCI in years when the SCI was published (1961 and 1964–1969).

(ii) *Pseudovisible citations*: citations from journals that were indexed in the SCI in 1961 but from years when the SCI was not published (1956–1960 and 1962–1963).

(iii) *Invisible citations* (*SCI years*): citations from journals that were not indexed in the SCI in years when the SCI was published (1961 and 1964–1969).

(iv) *Invisible citations* (*non-SCI years*): citations from journals that were not indexed in the SCI in 1961 and from years when the SCI was not published (1956–1960 and 1962–1963).

For our hypothetical scientist, this test considers six visible citations (dark blue in Table 4). It also considers two pseudovisible citations (dark red). Furthermore, it considers three invisible citations in SCI years (light blue). Finally, it considers three invisible citations in non-SCI years (light red).

For each scientist, we count the number of citations in these four sets and construct the corresponding percentile ranks. Using these measures, we estimate the following regression:

$$(2)\quad Dep.\ Rank_i = \delta_1 \cdot Visible\ Citations_i + \delta_2 \cdot Pseudovisible\ Citations_i$$
$$+ \theta_1 \cdot Invisible\ Citations\big(SCI\ years\big)_i + \theta_2 \cdot Invisible\ Citations\big(non\text{-}SCI\ years\big)_i$$
$$+ \pi \cdot Publications_i + Subject\ FE + \epsilon_i.$$

As pseudovisible citations were not visible to contemporaries, we would expect them to matter similarly to the invisible ones; that is, we would expect $\delta_1 \gg \delta_2 \approx \theta_1 \approx \theta_2$. Note that the comparison between visible and pseudovisible citations allows us to estimate the causal effect of citation metrics even if journals indexed in the SCI differed in quality from journals not indexed in the SCI.

We find that the coefficient on visible citations (Table 3, Specification 2) is almost identical to the baseline specification (Table 3, Specification 1). Strikingly, the coefficient on pseudovisible citations is a lot smaller and very similar to the coefficients on invisible citations. This indicates that citations in journals that were indexed by the SCI only had a differential impact in years in which the SCI was actually available. The coefficients on invisible citations from SCI years and non-SCI years are also very similar and not distinguishable from the coefficient on pseudovisible citations (p-value of test $\delta_2 = \theta_1 = \theta_2$: 0.941). Figure 5 visualizes the results of Specification 2. This confirms that citations from journals indexed by the SCI only mattered in years in which the SCI was available. In addition, in years when the SCI was not available, citations from journals indexed by the SCI (pseudovisible citations) did not differ from other invisible citations.

D. *Mechanisms*

In the next subsection, we shed light on two potential mechanisms that could underlie the increased assortative matching. First, scientists with few citations may have disproportionately left academia. Second, highly cited scientists may have moved up to better departments. We investigate these explanations in turn by comparing the impact of visible and invisible citations on these individual-level career outcomes.

Effect on Leaving Academia.—We start by estimating the impact of citation metrics on the probability of leaving academia. For these regressions, we study scientists whom we observe in the 1956 cross section of academics. We exclude scientists who were already full professors in 1956 to avoid picking up retirements.[21] We then check whether these scientists had left academia by 1969. We estimate the following regressions.

[21] The results are very similar if we include full professors in this analysis.

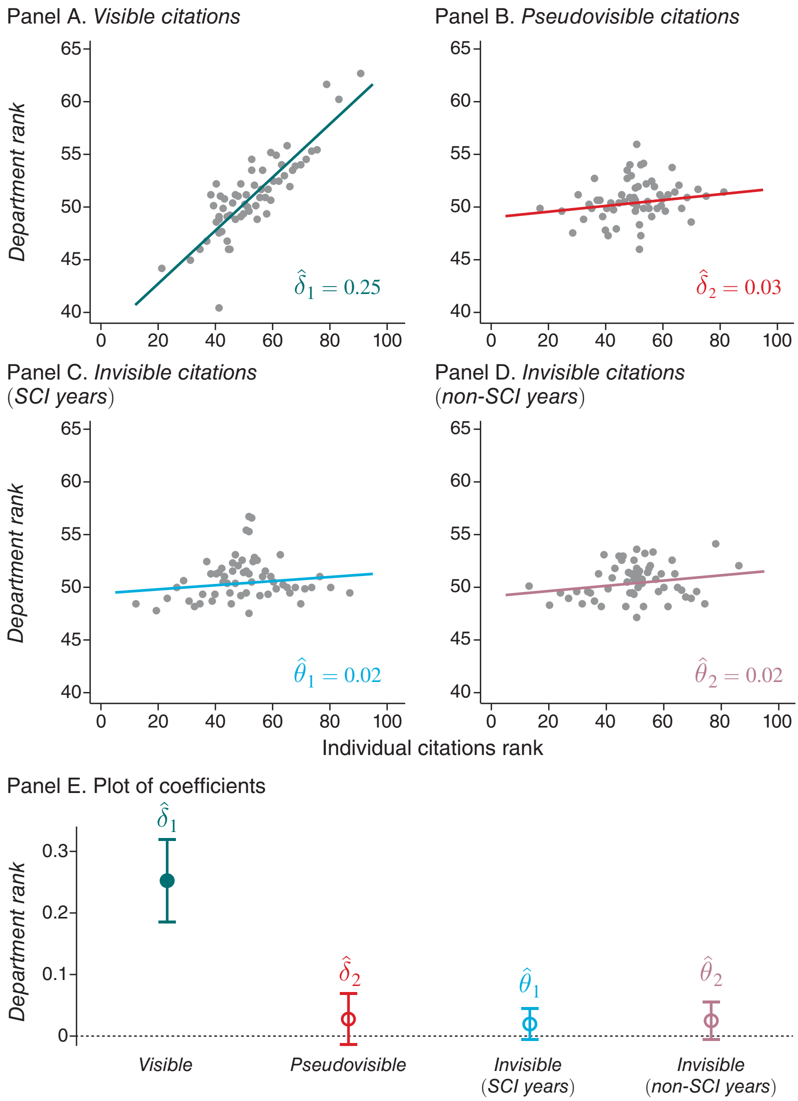

FIGURE 5. ASSORTATIVE MATCHING, SPECIFICATION 2

Notes: The figure illustrates the results from equation (2); see Table 3, Specification 2. Panels A to D report bin-scatterplots illustrating the relationship between citation ranks and the department rank. Panel E plots the coefficients and 95 percent confidence intervals.

SPECIFICATION 1:

$$(3)\quad \mathbb{1}\{Leaving\ Academia\}_i = \delta \cdot Visible\ Citations_i + \theta \cdot Invisible\ Citations_i + \pi \cdot Publications_i + Subject\ FE + \epsilon_i.$$

SPECIFICATION 2:

$$(4)\quad \mathbb{1}\{Leaving\ Academia\}_i = \delta_1 \cdot Visible\ Citations_i + \delta_2 \cdot Pseudovisible\ Citations_i + \theta_1 \cdot Invisible\ Citations\,(SCI\ years)_i + \theta_2 \cdot Invisible\ Citations\,(non\text{-}SCI\ years)_i + \pi \cdot Publications_i + Subject\ FE + \epsilon_i,$$

Table 5—Mechanism 1: Leaving Academia

	Dependent variable: *Leaving academia*				
	(1)	(2)	(3)	(4)	(5)
Panel A. Specification 1: Visible versus invisible citations					
Visible citations	−0.0038	−0.0042	−0.0038	−0.0034	−0.0033
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Invisible citations	0.0001	0.0008	0.0009	0.0010	0.0009
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
p-value (Visible = Invisible)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
R^2	0.088	0.092	0.105	0.244	0.297
Panel B. Specification 2: Visible versus pseudovisible versus invisible citations					
Visible citations	−0.0037	−0.0039	−0.0035	−0.0031	−0.0031
	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Pseudovisible citations	0.0002	0.0006	0.0006	0.0004	0.0004
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0006)
Invisible citations (SCI years)	−0.0002	−0.0000	0.0000	−0.0000	−0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Invisible citations (non-SCI years)	−0.0000	0.0001	0.0001	0.0002	0.0005
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
p-value (Visible = Pseudovisible)	< 0.001	< 0.001	< 0.001	0.001	0.001
p-value (Visible = Invisible (SCI years))	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
p-value (Visible = Invisible (non-SCI years))	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
p-value (Pseudovisible = Invisible (SCI) = Invisible (non-SCI))	0.718	0.510	0.579	0.810	0.521
R^2	0.089	0.092	0.105	0.244	0.297
Subject fixed effects	Yes	Yes	Yes	Yes	Yes
Publications by year		Yes			
Publications by year × subject			Yes	Yes	Yes
Publications by journal				Yes	
Publications by journal × subject					Yes
Observations	12,368	12,368	12,368	12,368	12,368
Dependent variable mean	0.691	0.691	0.691	0.691	0.691

Notes: The table reports the estimates of equation (3) in the first panel and of equation (4) in the second panel. The dependent variable is an indicator equal to one if scientist i left academia; that is, i was observed in 1956 but not in 1969. These regressions use the 1956 cross section of scientists who were not full professors. The explanatory variable *visible citations* measures scientist i's individual rank in the distribution of visible citations. *Invisible citations* measures scientist i's individual rank in the distribution of invisible citations. *Pseudovisible citations* measures scientist i's individual rank in the distribution of pseudovisible citations (citations in journals indexed in the SCI in 1961, but for years not covered in the SCI, i.e., 1956–1960 and 1962–1963). *Invisible citations* (*SCI years*) measures scientist i's individual rank in the distribution of invisible citations in SCI years (1961 and 1964–1969). *Invisible citations* (*non-SCI years*) measures scientist i's individual rank in the distribution of invisible citations in non-SCI years (citations in journals not indexed in the SCI in 1961 and in years that were not covered, i.e., 1956–1960 and 1962–1963). We transform ranks into percentiles, where 100 is the best and 1 the worst scientist. *Publications by year* separately measures the number of scientist i's publications in each year between 1956 and 1969. *Publications by journal* separately measures the number of scientist i's publications in each journal (e.g., *Nature*). Standard errors are clustered at the department level.

where $\mathbb{1}\{Leaving\ Academia\}_i$ is an indicator variable equal to one if a scientist left academia between 1956 and 1969. The remaining variable definitions are identical to the definitions in equations (1) and (2).

The probability of leaving academia was lower for academics with a higher visible citation count (Table 5, Specification 1). Scientists with a 10 percentile higher visible citation count were around 3.4 percentage points (or 5.0 percent relative to

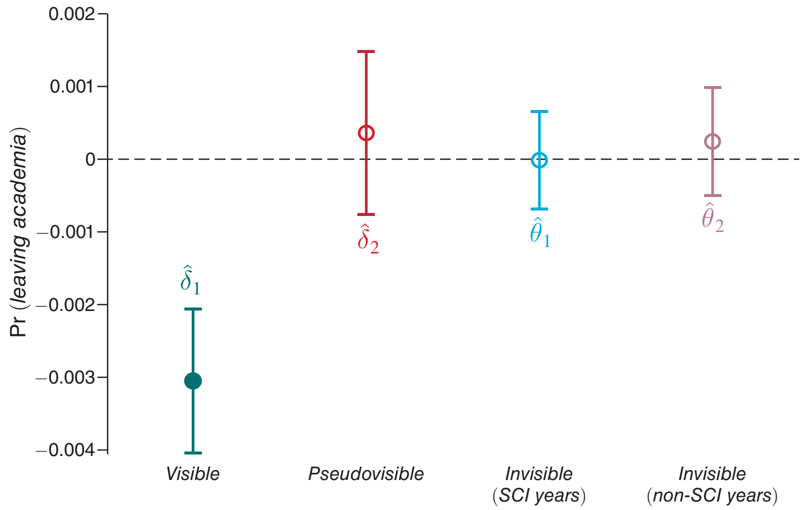

FIGURE 6. LEAVING ACADEMIA, SPECIFICATION 2

Note: The figure plots the coefficients and 95 percent confidence intervals from equation (4); see Table 5, Specification 2.

the mean) less likely to leave academia between 1956 and 1969. Strikingly, invisible citations did not have a significant impact on the probability of leaving academia. The p-values for the tests that the coefficients on visible and invisible citations are equal are lower than 0.001. The estimates from Specification 2 confirm these findings (Table 5, Specification 2, and Figure 6). These results suggest that the increased assortative matching of academics was, in part, driven by scientists with fewer visible citations leaving academia.

Effect on Moving to a Higher-Ranked Department.—As a second mechanism for increased assortative matching, we investigate the moves of scientists between departments. More specifically, we estimate variants of equation (3) and equation (4) in which we replace the dependent variable with an indicator that equals one if a scientist moved to a higher-ranked department between 1956 and 1969.

We find that scientists with a 10 percentile higher visible citation count were around 0.8 percentage points more likely to move to a higher-ranked department (Table 6, Specification 1). This relatively small point estimate nevertheless represents a 17.5 percent increase relative to the mean. Invisible citations did not affect the probability of moving to a higher-ranked department. The results are very similar if we estimate Specification 2 (Table 6, Specification 2, and Figure 7).

Only 4.6 percent of academics managed to move to a higher-ranked department between 1956 and 1969. Hence, some of the differences between the coefficients on visible and (the various) invisible citations are not significant at conventional levels. However, the results suggest that assortative matching also increased because scientists with many visible citations moved to higher-ranked departments.

Table 6—Mechanism 2: Moving to Higher-Ranked Department

	Dependent variable: *Moving to higher-ranked department*				
	(1)	(2)	(3)	(4)	(5)
Panel A. Specification 1: Visible versus invisible citations					
Visible citations	0.0008	0.0007	0.0006	0.0008	0.0007
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Invisible citations	−0.0001	0.0001	0.0000	−0.0003	−0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
p-value (Visible = Invisible)	0.101	0.254	0.238	0.078	0.154
R^2	0.014	0.018	0.037	0.336	0.405
Panel B. Specification 2: Visible versus pseudovisible versus invisible citations					
Visible citations	0.0008	0.0007	0.0006	0.0007	0.0006
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Pseudovisible citations	−0.0002	−0.0001	−0.0002	−0.0004	−0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
Invisible citations (SCI years)	0.0002	0.0002	0.0002	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Invisible citations (non-SCI years)	−0.0000	0.0000	0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
p-value (Visible = Pseudovisible)	0.027	0.076	0.076	0.059	0.147
p-value (Visible = Invisible (SCI years))	0.113	0.189	0.252	0.271	0.358
p-value (Visible = Invisible (non-SCI years))	0.015	0.050	0.102	0.134	0.281
p-value (Pseudovisible = Invisible (SCI) = Invisible (non-SCI))	0.498	0.625	0.519	0.389	0.564
R^2	0.014	0.018	0.037	0.336	0.405
Subject fixed effects	Yes	Yes	Yes	Yes	Yes
Publications by year		Yes			
Publications by year × subject			Yes	Yes	Yes
Publications by journal				Yes	
Publications by journal × subject					Yes
Observations	6,478	6,478	6,478	6,478	6,478
Dependent variable mean	0.046	0.046	0.046	0.046	0.046

Notes: The table reports the estimates of variants of equations (3) and (4) with a different dependent variable: an indicator equal to one if scientist i moved to a higher-ranked department between 1956 and 1969. These regressions use the sample of scientists observed in 1956 and 1969. The explanatory variable *visible citations* measures scientist i's individual rank in the distribution of visible citations. *Invisible citations* measures scientist i's individual rank in the distribution of invisible citations. *Pseudovisible citations* measures scientist i's individual rank in the distribution of pseudovisible citations (citations in journals indexed in the SCI in 1961 but for years not covered in the SCI, i.e., 1956–1960 and 1962–1963). *Invisible citations* (*SCI years*) measures scientist i's individual rank in the distribution of invisible citations in SCI years (1961 and 1964–1969). *Invisible citations* (*non-SCI years*) measures scientist i's individual rank in the distribution of invisible citations in non-SCI years (citations in journals not indexed in the SCI in 1961 and in years that were not covered, i.e., 1956–1960 and 1962–1963). We transform ranks into percentiles, where 100 is the best and 1 the worst scientist. *Publications by year* separately measures the number of scientist i's publications in each year between 1956 and 1969. *Publications by journal* separately measures the number of scientist i's publications in each journal (e.g., *Nature*). Standard errors are clustered at the department level.

E. *Overcoming Information Frictions across Geographic and Intellectual Distance*

The results on scientists who move up the department quality ladder also enable us to explore how citation metrics reduced information frictions. We would expect that citation metrics would matter more in situations where peers did not have good information on the quality of a potential hire.

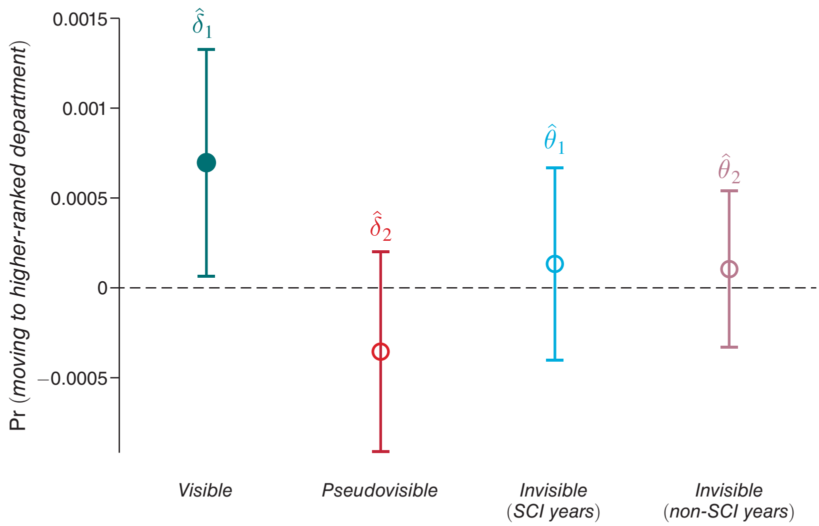

Figure 7. Moving to Higher-Ranked Department, Specification 2

Note: The figure plots the coefficients and 95 percent confidence intervals from a variant of equation (4) with an alternative dependent variable: an indicator for moving to a higher-ranked department; see Table 6, Specification 2.

We first investigate whether citation metrics help to overcome information frictions due to geographic distance. Specifically, we estimate two regressions with different dependent variables: (i) an indicator equal to 1 if scientist i moved to a higher-ranked department that was geographically far and (ii) an indicator equal to 1 if scientist i moved to a higher-ranked department that was geographically close. We define departments to be geographically far if they are more than 100km apart.[22] The results suggest that citation metrics only impacted moves to higher-ranked departments that were geographically far but not to departments that were geographically close (panel A of Figure 8 and online Appendix Table C.9).

We also investigate whether citation metrics helped to overcome information frictions due to intellectual distance. We measure intellectual distance using cross-department citations before the move of the scientist. Specifically, we measure whether scientist i's papers had been cited in the receiving department before the introduction of the SCI in 1963. We estimate two regressions with alternative dependent variables: (i) an indicator equal to 1 if scientist i moved to a higher-ranked department where i's research was not cited before the move and (ii) an indicator equal to 1 if scientist i moved to a higher-ranked department where i's research was cited at least once before the move.[23] The results suggest that citation metrics only impacted moves to higher-ranked departments where scientist i had not been cited before the move (panel B of Figure 8 and online Appendix Table C.10).

[22] Results are similar if we define departments as geographically close using alternative cutoffs (see online Appendix Figure C.3).

[23] Around a quarter of all moves to higher-ranked departments were to departments where scientists were cited before.

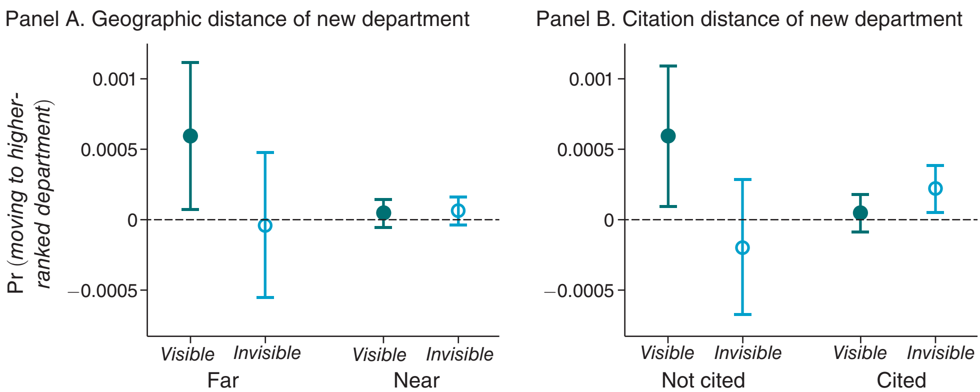

Figure 8. Moving to Higher-Ranked Departments by Geographic and Intellectual Distance

Notes: The figure plots coefficients and 95 percent confidence intervals from variants of equation (3). Panel A reports results from two regressions with alternative dependent variables: (i) an indicator for moving to a higher-ranked department that was far from scientist *i*'s department and (ii) an indicator for moving to a higher-ranked department that was close to scientist *i*'s department. Panel B reports results from two regressions with alternative dependent variables: (i) an indicator for moving to a higher-ranked department where scientist *i*'s papers were not cited before 1963 and (ii) an indicator for moving to a higher-ranked department where scientist *i*'s papers were cited before 1963. For detailed results, see online Appendix Tables C.9 and C.10.

Overall, these findings show that citation metrics helped overcome information frictions due to geographic and intellectual distance. Reducing these frictions may have enabled departments to discover scientists in lower-ranked departments, even if they had not interacted before.

III. Heterogeneous Impact of Performance Metrics

As the next step of our analysis, we investigate the heterogeneous impact of the SCI depending on the scientists' citation rank and the rank of their department. Furthermore, we investigate if minorities disproportionately profited from the availability of citation metrics.

A. *Heterogeneous Effects by Individual-Level Citation Rank*

First, we investigate if scientists in different percentiles benefited differentially from the visibility of their citations. Specifically, we estimate a nonparametric variant of our main regression:

$$(5) \quad Dep.\ Rank_i = \sum_q \delta_q \cdot \mathbb{1}\{Visible\ Cit\ Decile_i = q\} + \sum_q \theta_q \cdot \mathbb{1}\{Invisible\ Cit\ Decile_i = q\} + \pi \cdot Publications_i + Subject\ FE + \epsilon_i.$$

$\mathbb{1}\{Visible\ Cit\ Decile_i = q\}$ and $\mathbb{1}\{Invisible\ Cit\ Decile_i = q\}$ are indicator variables for i's decile in the visible and invisible citation distributions, respectively.

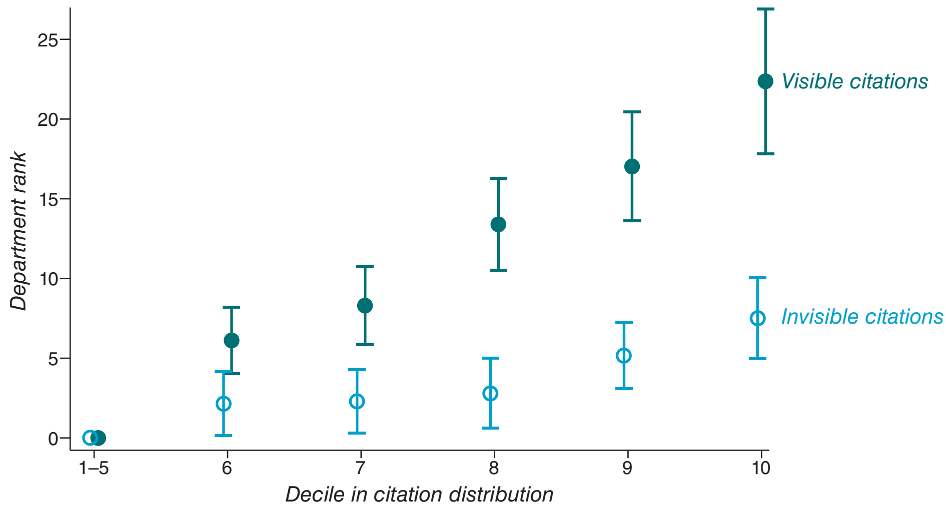

Figure 9. Heterogeneous Effects by Individual-Level Citation Rank

Note: The figure plots coefficients $\hat{\delta}_q$ (dark blue) and $\hat{\theta}_q$ (light blue) and 95 percent confidence intervals from equation (5).

We visualize the estimates relative to the bottom half of the visible and invisible individual-level citation distribution (Figure 9).[24]

Over the upper half of the citation distribution, an increase in visible citations increases the assortativeness of the match between the rank of scientist *i* and the rank of her department. Furthermore, the gap between visible and invisible citations widens for higher deciles of the citation distribution. A scientist in the top decile of the visible citation distribution was, on average, placed in a department that was 22.4 percentiles higher in the department ranking, compared to scientists in the bottom half of the visible citation distribution. This is equivalent to a physicist being placed at Harvard as opposed to Case Western Reserve University. In contrast, a scientist in the top decile of the invisible citation distribution was, on average, placed in a department that was only seven percentiles higher ranked, compared to a scientist in the bottom half of the invisible citation distribution. In online Appendix Figure D.1, we further split up the top decile and show that scientists in the very highest percentiles of the visible citation distribution are placed in even higher-ranked departments. These results suggest that scientists at the upper end of the citation distribution had a particularly large benefit from the availability of citation metrics.

[24] To save space, we report results for the specification that controls for the number of publications by year and subject, equivalent to column 3 of Table 3. The results for the other specifications are almost identical. Because in some subjects, e.g., mathematics, a relatively high fraction of scientists have zero citations, we do not separately estimate effects for lower deciles.

B. *Heterogeneous Effects for Peripheral Scientists*

Second, we analyze if scientists who were placed in lower-ranked departments (peripheral scientists) in 1956 differentially benefited from the availability of citation metrics. For this test, we restrict the sample to scientists whom we observe both in 1956 and in 1969. The outcome variable is their department rank in 1969:

$$(6)\quad Dep.\ Rank_i = \sum_q \delta_q^H \cdot \mathbb{1}\{Visible\ Cit\ Decile_i = q\} \times High\text{-}Ranked(1956)_i$$
$$+ \sum_q \delta_q^L \cdot \mathbb{1}\{Visible\ Cit\ Decile_i = q\} \times Low\text{-}Ranked(1956)_i$$
$$+ \sum_q \theta_q^H \cdot \mathbb{1}\{Invisible\ Cit\ Decile_i = q\} \times High\text{-}Ranked(1956)_i$$
$$+ \sum_q \theta_q^L \cdot \mathbb{1}\{Invisible\ Cit\ Decile_i = q\} \times Low\text{-}Ranked(1956)_i$$
$$+ \omega \cdot Low\text{-}Ranked(1956)_i + \pi \cdot Publications_i$$
$$+ Subject\ FE + \epsilon_i.$$

Variable definitions are identical to equation (5). We add interactions between the deciles of the individual-level citation distributions with indicator variables that equal one if the scientist was working in either a high-ranked or a low-ranked department in 1956. We also control for the main effect of working in a low-ranked department in 1956. We define low-ranked departments as those below the seventy-fifth percentile of the department ranking.[25] In physics, for example, low-ranked departments are all departments that were ranked lower than the University of Wisconsin, Madison.

We show estimates for the deciles of the visible citation distribution for scientists in high-ranked and low-ranked departments in Figure 10.[26] Estimates for scientists in low-ranked departments are consistently larger than for scientists in high-ranked departments. The *p*-values for the tests that coefficients for the top two deciles are the same in low-ranked and high-ranked departments are below 0.001. This indicates that scientists who were in lower-ranked departments in 1956 benefited disproportionately from the availability of citation metrics.[27]

In other words, citation metrics enabled the discovery of "hidden stars." This may have reduced misallocation by helping the highest-cited scientists in low-ranked departments to move to high-ranked departments. This finding is consistent with

[25] Results are qualitatively similar if we use alternative cutoffs (e.g., sixtieth, seventieth, eightieth, or ninetieth percentile; see online Appendix Figure D.2).

[26] To improve clarity, the figure does not report the estimates for the invisible citation deciles. As in Figure 9, the estimates for invisible citations are consistently smaller than for visible citations. We also find no difference in the impact of invisible citations depending on the department rank.

[27] These effects may be interpreted as mechanical because scientists in low-ranked departments in 1956 have more scope to move to a higher-ranked department. Nevertheless, it is important to quantify how "hidden stars" may benefit from the availability of performance metrics.

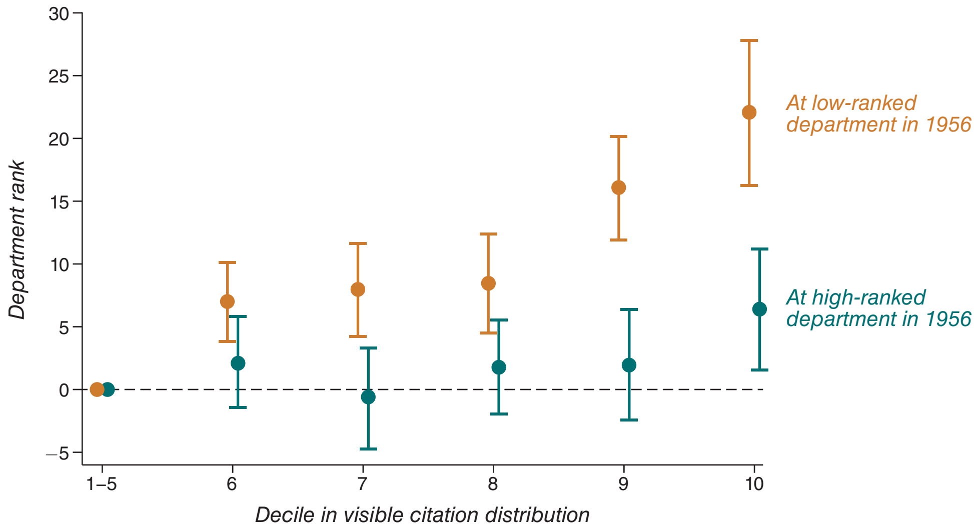

Figure 10. Heterogeneous Effect of Citation Rank for Peripheral Scientists

Note: The figure plots coefficients $\hat{\delta}_q^H$ (orange) and $\hat{\delta}_q^L$ (blue) and 95 percent confidence intervals from equation (6).

anecdotal evidence; for example, a contemporary scientist remarked that "[t]he SCI was especially useful to find people who would otherwise be overlooked" (as cited in Wouters 1999b, p. 138).

One example of such a "hidden star" is the medical scientist Hans Hecht. Swiss-born, he obtained his MD in Germany in 1936. He escaped the Nazi regime in 1938 and emigrated to the United States.[28] He started his US career as an "Instructor of Medicine at the Wayne University School of Medicine, following which he moved to the University of Utah, where, in 1946, he earned a second M.D. degree" (Katz 1971) and became a professor there. Arnold Katz of the Mount Sinai School of Medicine described that his "breadth of scientific interests […] was always based on an extraordinarily high level of scientific excellence […] he was never taken in by the investigator with a long list of unoriginal or superficial papers, but saw clearly the essential quality of a man's work" (Katz 1971). In the mid-1960s, Hans Hecht was hired by the University of Chicago.

We explore whether the example of Hans Hecht indeed provides more general insights into the characteristics of "hidden stars." That is, we investigate which characteristics are correlated with being underplaced before the availability of citation metrics. For this analysis, we define star scientists as scientists whose total citations (both visible and invisible) place them in the top 5 percent of the subject-level citation distribution in 1969. For these 450 scientists, we can infer some characteristics from our data, e.g., whether they were female, but also whether they were of Asian, Hispanic, or Jewish origin. We measure these characteristics

[28] See Becker et al. (2024) for the emigration of scientists from Nazi Germany.

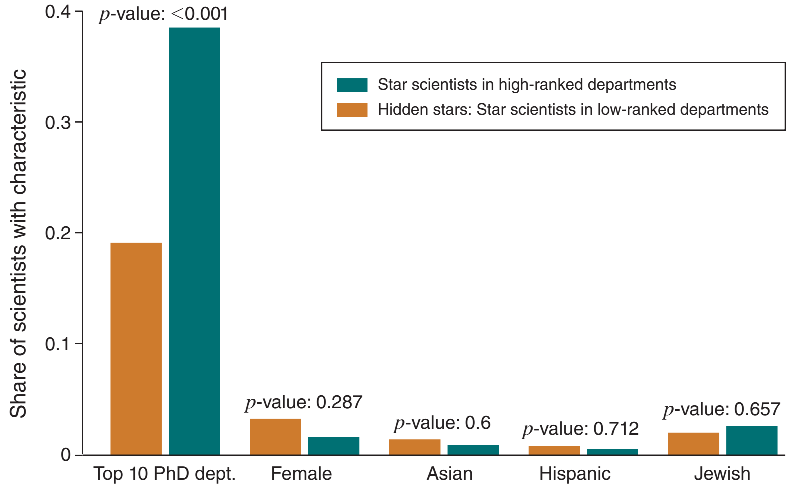

Figure 11. Characteristics of "Hidden Stars" and Other Star Scientists

Notes: The figure reports characteristics of star scientists who were in high-ranked departments (blue) and low-ranked departments ("hidden stars," orange) in 1956. As before, low-ranked departments are those below the seventy-fifth percentile of the department ranking in 1956. For this figure, we define star scientists as all scientists in the top 5 percent of the subject-level citation distribution.

based on the names of academics (for more details, see online Appendix B.1). In addition, we collect information on where these star scientists obtained their PhD through an extensive web search.[29]

We then report the average characteristics of star scientists in high-ranked departments and of star scientists who worked in low-ranked departments in 1956 ("hidden stars"). Thirty-eight percent of star scientists in high-ranked departments had received a PhD from a top 10 department in the United States. In contrast, only 18 percent of "hidden stars" had received a PhD from a top 10 department (Figure 11). We also find that there were twice as many women among "hidden stars." Since there were very few women in academia at the time (Iaria, Schwarz, and Waldinger 2022), the difference is not statistically significant. Overall, this evidence suggests that "hidden stars" had, on average, obtained their PhD from worse universities and that they were more likely to be female.

C. *Heterogeneous Effects for Minority Scientists*

In the last part of this section, we investigate the heterogeneous impacts of citation metrics on minority scientists. Specifically, we analyze whether women, Hispanics, Asians, and Jews disproportionately benefited from the availability of citation metrics. As outlined above, we identify these groups based on the names of academics. As the proportion of minorities among academics was low in the 1960s (e.g., Card

[29] We obtain the PhD university for 400 out of the 450 star scientists.

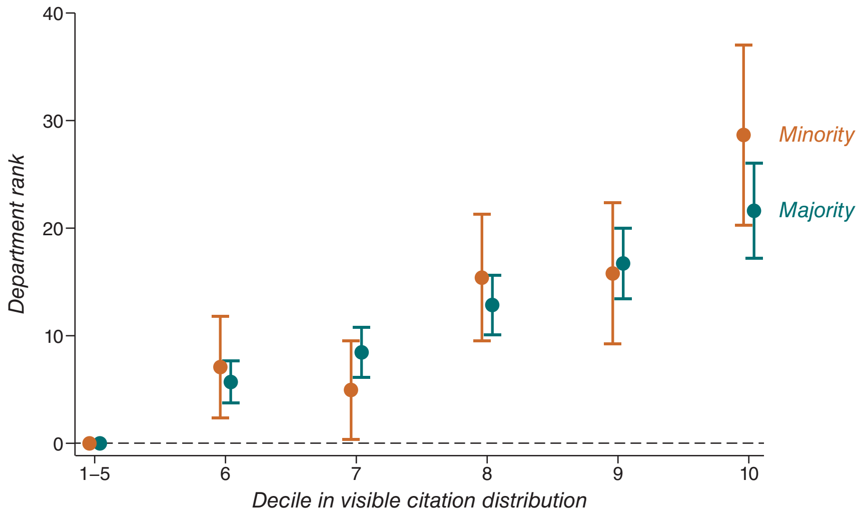

FIGURE 12. HETEROGENEOUS EFFECTS FOR MAJORITY AND MINORITY SCIENTISTS

Note: The figure plots coefficients $\hat{\delta}_q^M$ (blue) and $\hat{\delta}_q^m$ (orange) and 95 percent confidence intervals from equation (7).

et al. 2023; Iaria, Schwarz, and Waldinger 2022), we pool all minorities to gain power. We then estimate the following regression:

$$(7) \quad Dep.\ Rank_i = \sum_q \delta_q^M \cdot \mathbb{1}\{Visible\ Cit\ Decile_i = q\} \times Majority_i$$
$$+ \sum_q \delta_q^m \cdot \mathbb{1}\{Visible\ Cit\ Decile_i = q\} \times Minority_i$$
$$+ \sum_q \theta_q^M \cdot \mathbb{1}\{Invisible\ Cit\ Decile_i = q\} \times Majority_i$$
$$+ \sum_q \theta_q^m \cdot \mathbb{1}\{Invisible\ Cit\ Decile_i = q\} \times Minority_i$$
$$+ \omega \cdot Minority_i + \pi \cdot Publications_i + Subject\ FE + \epsilon_i.$$

Variables are defined as before, but we add interactions with indicator variables that equal one if the scientist belonged either to the majority or to the minority. We also control for an indicator that equals one if the scientists belonged to a minority.

While we do not find evidence that minority scientists, on average, benefited more from citation metrics than majority scientists (online Appendix Table D.2), the evidence in Figure 12 suggests that among star scientists (top decile) minority scientists benefit slightly more than majority scientists.[30] The p-value for the test

[30] The democratizing effect of citation metrics is driven by larger effects of citation metrics for women and Jews (see online Appendix Figure D.3). These results are robust to adding a control for the department rank of scientist i in 1956 (online Appendix Figure D.4).

that the coefficients for the tenth decile are the same for minority and majority scientists is 0.051.

Taken together, these results suggest that the availability of more "objective" performance metrics helped disadvantaged high-quality scientists. In particular, highly cited scientists in lower-ranked departments ("hidden stars") and highly cited minority scientists benefited from the availability of citation metrics.

IV. Impact of Performance Metrics on Careers

As shown above, citation metrics increased assortative matching between scientists and departments. In the last part of the paper, we study whether scientists with more visible citations also accrued additional benefits. We investigate such benefits by studying the impact of citation metrics on promotions and receiving NSF grants. This analysis also speaks to whether citation metrics increased recognition by peers and the wider scientific community, suggesting Matthew effects (Merton 1968). We estimate the following regressions:

SPECIFICATION 1:

$$\mathbb{1}\{\textit{Career Outcome}\}_i = \delta \cdot \textit{Visible Citations}_i + \theta \cdot \textit{Invisible Citations}_i + \pi \cdot \textit{Publications}_i + \textit{Subject FE} + \epsilon_i; \tag{8}$$

SPECIFICATION 2:

$$\begin{aligned} \mathbb{1}\{\textit{Career Outcome}\}_i = {} & \delta_1 \cdot \textit{Visible Citations}_i + \delta_2 \cdot \textit{Pseudovisible Citations}_i \\ & + \theta_1 \cdot \textit{Invisible Citations}(\textit{SCI years})_i + \theta_2 \cdot \textit{Invisible Citations}(\textit{non-SCI years})_i \\ & + \pi \cdot \textit{Publications}_i + \textit{Subject FE} + \epsilon_i, \end{aligned} \tag{9}$$

where $\mathbb{1}\{\textit{Career Outcome}\}_i$ is an indicator that equals one if the scientist was promoted or received an NSF grant. The remaining variable definitions are identical to equations (1) and (2).

A. *Effect on Promotions*

We investigate if scientists whom we observe as assistant or associate professors in 1956 were promoted to full professors by 1969. This allows us to directly study how the introduction of performance metrics influenced academic careers and peer recognition. We estimate equations (8) and (9), where the dependent variable equals one if scientist *i* was promoted to full professor between 1956 and 1969.

We find that the visible citation rank has a significant positive impact on promotions (Table 7). The probability of promotion increased by 4.1 percentage points (or 5.8 percent relative to the mean) for scientists with a 10 percentile higher visible

Table 7—Promotion to Full Professor

	Dependent variable: *Promotion to full professor*				
	(1)	(2)	(3)	(4)	(5)
Panel A. Specification 1: Visible versus invisible citations					
Visible citations	0.0042	0.0046	0.0047	0.0041	0.0040
	(0.0006)	(0.0007)	(0.0007)	(0.0010)	(0.0013)
Invisible citations	0.0009	0.0003	0.0004	−0.0003	−0.0001
	(0.0005)	(0.0006)	(0.0006)	(0.0010)	(0.0012)
p-value (Visible = Invisible)	0.002	< 0.001	< 0.001	0.017	0.068
R^2	0.140	0.145	0.154	0.366	0.395
Panel B. Specification 2: Visible versus pseudovisible versus invisible citations					
Visible citations	0.0043	0.0048	0.0048	0.0041	0.0041
	(0.0006)	(0.0006)	(0.0007)	(0.0010)	(0.0013)
Pseudovisible citations	0.0000	−0.0004	−0.0003	−0.0002	0.0001
	(0.0006)	(0.0006)	(0.0006)	(0.0011)	(0.0012)
Invisible citations (SCI years)	0.0006	0.0005	0.0005	0.0006	0.0006
	(0.0005)	(0.0005)	(0.0005)	(0.0009)	(0.0011)
Invisible citations (non-SCI years)	0.0003	0.0001	0.0002	−0.0007	−0.0011
	(0.0005)	(0.0005)	(0.0005)	(0.0009)	(0.0011)
p-value (Visible = Pseudovisible)	< 0.001	< 0.001	< 0.001	0.017	0.068
p-value (Visible = Invisible (SCI years))	< 0.001	< 0.001	< 0.001	0.015	0.054
p-value (Visible = Invisible (non-SCI years))	< 0.001	< 0.001	< 0.001	< 0.001	0.002
p-value (Pseudovisible = Invisible (SCI) = Invisible (non-SCI))	0.755	0.541	0.663	0.678	0.655
R^2	0.140	0.146	0.154	0.366	0.395
Subject fixed effects	Yes	Yes	Yes	Yes	Yes
Publications by year		Yes			
Publications by year × subject			Yes	Yes	Yes
Publications by journal				Yes	
Publications by journal × subject					Yes
Observations	3,364	3,364	3,364	3,364	3,364
Dependent variable mean	0.707	0.707	0.707	0.707	0.707

Notes: The table reports the estimates of equation (8) in the first panel and of equation (9) in the second panel. The dependent variable is an indicator equal to one if scientist *i* was promoted to full professor between 1956 and 1969. These regressions use the sample of scientists observed in 1956 and 1969 who were not full professors in 1956. The explanatory variable *visible citations* measures scientist *i*'s individual rank in the distribution of visible citations. *Invisible citations* measures scientist *i*'s individual rank in the distribution of invisible citations. *Pseudovisible citations* measures scientist *i*'s individual rank in the distribution of pseudovisible citations (citations in journals indexed in the SCI in 1961 but for years not covered in the SCI, i.e., 1956–1960 and 1962–1963). *Invisible citations* (*SCI years*) measures scientist *i*'s individual rank in the distribution of invisible citations in SCI years (1961 and 1964–1969). *Invisible citations* (*non-SCI years*) measures scientist *i*'s individual rank in the distribution of invisible citations in non-SCI years (citations in journals not indexed in the SCI in 1961 and in years that were not covered, i.e., 1956–1960 and 1962–1963). We transform ranks into percentiles, where 100 is the best and 1 the worst scientist. *Publications by year* separately measures the number of scientist *i*'s publications in each year between 1956 and 1969. *Publications by journal* separately measures the number of scientist *i*'s publications in each journal (e.g., *Nature*). Standard errors are clustered at the department level.

citation rank.[31] The estimates for invisible citations are close to zero and statistically insignificant. The estimates from Specification 2 confirm these findings (Table 7 and panel A of Figure 13).

[31] The effect of citation metrics on promotions is estimated within the set of academics whom we observe in 1956 and who have not left academia by 1969. Since the probability of leaving academia decreases with visible citations (see Section IID), we likely estimate a lower bound of the effect of citation metrics on promotions.

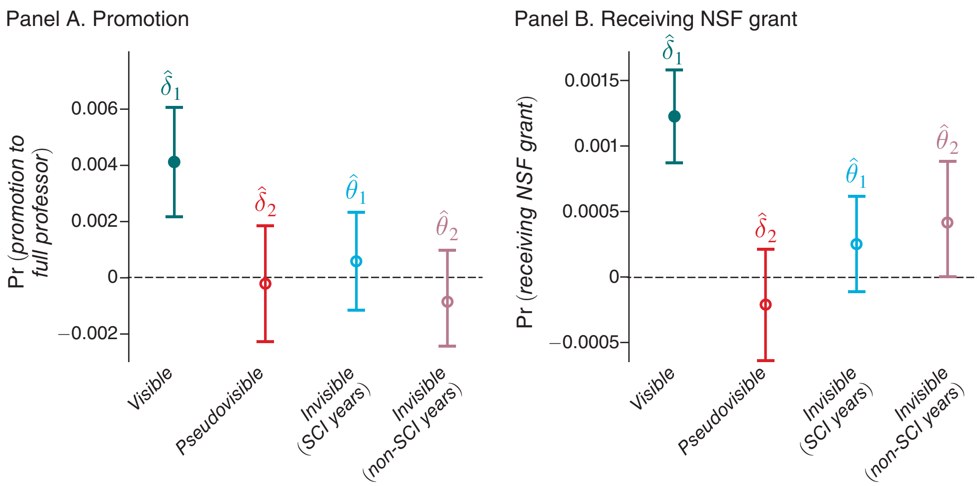

Figure 13. Effect on Career Outcomes, Specification 2

Note: The figure plots coefficients and 95 percent confidence intervals from variants of equation (9); see Table 7 and Table 8, Specification 2.

The results indicate that departments indeed used citation metrics in promotion decisions. As full professor positions come with many advantages, such as prestige, job security, and research funds, these findings suggest that citation metrics affected individual careers and the allocation of resources in the sciences.

B. *Effect on Research Grants*

Finally, we investigate the effect of citation metrics on receiving research grants. This analysis examines whether citation metrics affect the allocation of resources and recognition by the wider scientific community. We digitize entries of all grants awarded in 1969 by the National Science Foundation (NSF) and match them to the scientists in our faculty rosters (see online Appendix B.1.3). We estimate equations (8) and (9), where the dependent variable equals one if scientist i received at least one NSF grant.[32]

The visible citation rank has a significant positive impact on receiving NSF grants (Table 8). The probability of receiving a grant increased by 1.3 percentage points (or 19.0 percent relative to the mean) for scientists with a 10 percentile higher visible citation rank. The estimates for invisible citations are close to zero and statistically insignificant. The estimates from Specification 2 confirm these findings (Table 8 and panel B of Figure 13).

These results highlight that the effects of citation metrics go beyond the allocation of talent: they affect whether scientists are promoted and whether they receive research grants. Thus, recognition through citations enables high-performing scientists to accrue additional rewards and resources, contributing to Matthew effects in the sciences (Merton 1968).

[32] We exclude medical scientists from this analysis because the NSF does not fund research in medicine. If we include medical researchers, the results are very similar (see online Appendix Table E.1).

Table 8—Receiving an NSF Grant

	Dependent variable: *Receiving NSF grant*				
	(1)	(2)	(3)	(4)	(5)
Panel A. Specification 1: Visible versus invisible citations					
Visible citations	0.0021	0.0017	0.0015	0.0013	0.0012
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Invisible citations	0.0003	−0.0000	−0.0000	0.0001	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
p-value (*Visible* = *Invisible*)	< 0.001	< 0.001	< 0.001	0.001	0.002
R^2	0.064	0.070	0.086	0.215	0.249
Panel B. Specification 2: Visible versus pseudovisible versus invisible citations					
Visible citations	0.0020	0.0017	0.0015	0.0012	0.0012
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Pseudovisible citations	−0.0004	−0.0005	−0.0005	−0.0002	−0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Invisible citations (SCI years)	0.0003	0.0001	0.0003	0.0003	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Invisible citations (non-SCI years)	0.0007	0.0005	0.0005	0.0004	0.0005
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
p-value (Visible = Pseudovisible)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
p-value (Visible = Invisible (SCI years))	< 0.001	< 0.001	< 0.001	0.001	0.003
p-value (Visible = Invisible (non-SCI years))	< 0.001	< 0.001	0.002	0.009	0.022
p-value (Pseudovisible = Invisible (SCI) = Invisible (non-SCI))	0.005	0.016	0.005	0.200	0.222
R^2	0.066	0.071	0.087	0.215	0.249
Subject fixed effects	Yes	Yes	Yes	Yes	Yes
Publications by year		Yes			
Publications by year × subject			Yes	Yes	Yes
Publications by journal				Yes	
Publications by journal × subject					Yes
Observations	15,582	15,582	15,582	15,582	15,582
Dependent variable mean	0.068	0.068	0.068	0.068	0.068

Notes: The table reports the estimates of equation (8) in the first panel and of equation (9) in the second panel. The dependent variable is an indicator equal to one if scientist i received an NSF grant in 1969. These regressions use the sample of scientists observed in 1969, excluding medicine. The explanatory variable *visible citations* measures scientist i's individual rank in the distribution of visible citations. *Invisible citations* measures scientist i's individual rank in the distribution of invisible citations. *Pseudovisible citations* measures scientist i's individual rank in the distribution of pseudovisible citations (citations in journals indexed in the SCI in 1961 but for years not covered in the SCI, i.e., 1956–1960 and 1962–1963). *Invisible citations* (*SCI years*) measures scientist i's individual rank in the distribution of invisible citations in SCI years (1961 and 1964–1969). *Invisible citations* (*non-SCI years*) measures scientist i's individual rank in the distribution of invisible citations in non-SCI years (citations in journals not indexed in the SCI in 1961 and in years that were not covered, i.e., 1956–1960 and 1962–1963). We transform ranks into percentiles, where 100 is the best and 1 the worst scientist. *Publications by year* separately measures the number of scientist i's publications in each year between 1956 and 1969. *Publications by journal* separately measures the number of scientist i's publications in each journal (e.g., *Nature*). Standard errors are clustered at the department level.

V. Conclusion

The evaluation of scientists based on performance metrics, and in particular citations, has become ubiquitous in modern science. Scientists are highly aware of the number of citations their papers have received, and standard metrics such as the impact factor or the h-index are not only used to evaluate scientists and papers but also influence hiring and promotion decisions. Equally, departments and scientific journals are frequently ranked based on citation measures. This widespread reliance on citation metrics has been criticized, as citations only capture one dimension of an academic's contribution to knowledge (DORA 2013; CoARA 2022). Despite these concerns, little is known about the consequences of measuring citations for scientific careers and the allocation of talent and resources.

In this paper, we use the introduction of the *Science Citation Index* to provide the first causal estimates of how citation metrics affect the organization of science. We develop a new identification strategy to show that systematically measuring and revealing citations had a large and immediate impact on the careers of scientists. First, we show that the introduction of citation metrics increased assortative matching between scientists and departments based on citations by reducing information frictions. Second, we show that the effect was particularly pronounced for scientists in the top end of the citation distribution, and especially for "hidden stars" (highly cited scientists in lower-ranked departments), as well as for highly cited minority scientists. Finally, we show that measuring citations increased the reliance on citation metrics in promotion decisions and in allocating research grants. Overall, our findings demonstrate that citation metrics have a profound impact on the organization of modern science.

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