Measuring Science: Performance Metrics and the Allocation of Talent*

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April 21, 2023

Abstract

We study how performance metrics affect the allocation of talent. We exploit the introduction of a new measure of scientific performance: citation metrics. For technical reasons, the first citation database only covered citations from certain journals and years. Thus, only a subset of 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. We also find that highly-cited scientists in lower-ranked departments ("hidden stars") benefited from citation metrics, while minorities did not. Citation metrics also affected promotion decisions.

*We thank Ran Abramitzky, Nano Barahona, David Card, Stefano DellaVigna, Lena Greska, Elena Heller, Pat Kline, Robin Mamrak, Ted Miguel, Abhishek Nagaraj, Marco Ottaviani, Ricardo Perez-Truglia, Simon Quinn, Jesse Rothstein, Carolyn Stein, Claudia Steinwender, Steve Tadelis, Maria Waldinger, Chris Walters, Joachim Winter, Noam Yuchtman, and seminar audiences at Berkeley Haas, Berkeley, Berlin, Bocconi, CERGE-EI, HEC, LMU Munich, and the 2023 BITSS Annual Meeting for insightful comments and suggestions. We are grateful to Alessandro Iaria, a member of our wider research team that has collected the World of Academia Database, which we use in this paper. Matthias Bing, Peter Heinrich, Paulina Meier, and Nils Süßenbach provided excellent research assistance.

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1 Introduction

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 et al., 1991; Jones, 1995; Weitzman, 1998; Romer, 1986, 1990). As talent is scarce, private sector firms and universities increasingly rely on performance metrics to identify talented individuals (e.g., Hoffman et al., 2018; Forbes, 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 the importance of such metrics, as well as the recent discussions, there is virtually no evidence of 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. Our empirical strategy exploits the introduction of the *Science Citation Index* (SCI), which led to quasi-random variation in the visibility of individual scientists' citations.

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 dramatically in 1963 when Eugene Garfield published the first *Science Citation Index* (SCI). For the first time, it became possible to identify the highest-cited papers and researchers. The Nobel Laureate and molecular biologist Joshua Lederberg welcomed the first edition of the SCI with the words: "I think you're making history, Gene!" (Wouters, 2017). 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" (Carlton, 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' citations and the ranking of their department increased by 54%. At the same time, scientists' publications became 36% less predictive of their department ranking. These over-time changes suggest that hiring committees started to attach more weight to citation counts and less weight to publication counts 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 or 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 et al., 2007; Jones, 2009) may have spurred within-department collaborations 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 journals and years. 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 coverage of citations (1) over time and (2) across journals. First, citations appearing in cit*ing* articles until 1960 were invisible. With the first edition of the SCI, citations from citing articles in 1961 became visible. Due to technological 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 (but are observable today). 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 onwards) remained invisible if they came from citing articles published in journals not indexed by the SCI. Importantly, 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 cit*ed* 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 each of the two 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

[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).

in 1962, the first citation became visible in the SCI, while the second remained invisible to contemporaries. Using modern citation databases, we can, however, observe both visible and invisible citations.

To carry out our empirical analysis, we combine new data on historical faculty rosters of U.S. universities from the *World of Academia Database* (Iaria et al., 2022) with extensive publication and citation data from *Clarivate Web of Science*. These data enable us to construct the most comprehensive individual and department-level 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 importance of visible citations relative to invisible citations. The identification strategy relies on the assumption that visible and invisible citations would be equally predictive of career outcomes, had the SCI not become available in the 1960s. 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 2.6 percentiles higher ranked department in 1969. For instance, a chemist would be placed at Harvard or Berkeley as opposed to the University of Illinois Urbana-Champaign or Michigan. In contrast, scientists with a 10 percentile higher invisible citation count were on average only placed at a 0.7 percentiles higher ranked department. This pattern holds even if we control for detailed publication records, i.e., for the number of publications in each journal (e.g., two *Nature*, one *Science*, and one *PNAS* publication) and year (e.g., one publication in 1956, two in 1958, and one in 1960). 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, a concern with this empirical strategy could be that the visibility of citations in the SCI was correlated with other characteristics that impact career outcomes. First, visible citations may come from citing articles in higher quality journals (e.g., *Nature* or *Science*) and may therefore have a larger impact on scientists' careers. In a robustness check, we abstract from potential differences in journal quality by relying exclusively on over-time variation in visibility. 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. The results remain unchanged, indicating that differences in the quality of indexed journals cannot explain our findings.

Second, as the SCI was introduced in 1961, visible citations are more likely to occur in later years. This would bias our estimates if citations in later years had a larger impact on scientists' career outcomes in 1969. To address this concern, we exclusively rely on across-journal variation in the visibility of citations. This robustness check 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 visible in the SCI, while the other citation occurred in *Chemical Reviews*, and was invisible. The results remain unchanged, indicating that differences in the timing of citations cannot explain our findings.

Further, we investigate whether citations that would have been visible, had the SCI been introduced earlier, have any predictive power. We construct "pseudo-visible" citations, i.e., citations from journals that were covered in the first SCI, but in years in which the SCI was not published. This placebo test compares pseudo-visible and invisible citations for years in which the SCI did not yet exist. The results show that citations in journals covered by the SCI did not matter differentially in years in which the SCI was not yet available. This provides strong evidence for our identifying assumption because the differential impact of visible citations, relative to invisible ones, only occurs for years that were actually covered in the SCI.[2]

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 2.9 percentage points (or 4.2 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 0.6 percentage points (or 11.6 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.

[2]We also show that our findings are robust to using alternative functional forms of the citation measures and to measuring department quality with alternative department rankings.

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 90th 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, citations 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 to move to higher-ranked departments. Third, we investigate if minorities differentially benefited from the introduction of the SCI. We find that neither female, Hispanic, Asian, nor Jewish academics benefited disproportionately from the availability of citation metrics. These results suggest that the availability of more "objective" performance metrics did not help minorities overcome potential discrimination.

In the last part of the article, we study the impact of citation metrics on individual-level promotions. We analyze whether scientists who were assistant or associate professors in 1956 were promoted to full professors by 1969. We find that the probability of promotion increased by 4.5 percentage points (or 6.3 percent) for scientists with a 10 percentile higher visible citation rank. In contrast, invisible citations did not affect promotion probabilities. These results indicate that the introduction of citation metrics not only affected assortative matching but also had direct impacts on the careers of scientists. As full professor positions come with higher salaries, job security, and improved access to research grants, citation metrics also changed the allocation of resources to individual scientists.

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 et al., 2018). Additional contributions have highlighted the importance of superstar scientists (Azoulay et al., 2010), studied whether peer-effects affect 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 et al., 2014; Jin et al., 2019), gatekeepers (Azoulay et al., 2019), or discrimination (e.g., Card et al., 2020, 2022; Iaria et al., 2022; Koffi, 2021; Hengel, 2022).

Despite all these papers making use of publication and citation data, and a long-standing debate on citations in sociology (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 evidence on how the observability of citation metrics affect scientific careers. While some papers have documented that citation metrics, such as the h-index or citation counts, predict career outcomes (e.g., Ellison, 2013; Jensen et al., 2009; Hilmer et al., 2015), our paper is the first to causally examine this fundamental aspect of modern science. Specifically, we disentangle differences in the *underlying* quality of academics from differences in the *observed* quality on the basis of citation metrics. Our results highlight that the *observability* is of crucial importance.

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 et al., 2022). The unique advantage of our setting is that we observe the information set available to decision-makers at the time – and crucially, what was not part of that information set.[3]

Last, we contribute to research on assortative matching in the labor market (e.g., Abowd et al., 1999; Andrews et al., 2008; Card et al., 2013; Song et al., 2019) by showing that performance metrics can increase assortative matching.

2 The Science Citation Index: Background and Data

2.1 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 In-*

[3]Since we measure the exact 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).

formation (ISI) developed the technology to construct a citation index. By the early 1960s, this undertaking was supported by National Institutes of Health and National Science Foundation grants. In November 1963, these efforts came to fruition and the first edition of the SCI was published, covering citations in 1961 (Garfield, 1963b, see Figure 1, panel (a), for a picture of the first SCI). The SCI quickly became the "most widely used and authoritative database of research publications and citations" (Birkle et al., 2020).

To construct the SCI, Garfield and his team selected 613 cit*ing* journals from the physical and life sciences and collected all citations appearing in articles in these journals in 1961 (Garfield, 1963a). This enabled them to identify all papers that were cited by these articles in 1961. The cit*ed* 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 and printed by IBM computers (Garfield (1963b), p. x). Entries were ordered by the last name and initials of each scientist (see Figure 1, panel (c)). Figure 1, panel (b), shows the 1961 entry for the medical scientist Murray R. 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.[4] From then on, the SCI was published quarterly. The set of covered cit*ing* journals quickly expanded from 613 in 1961 to 2,180 in 1969.

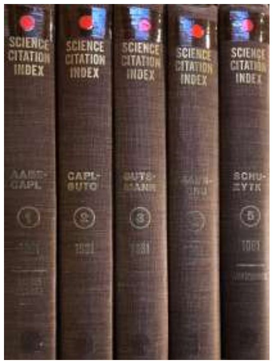
Despite its relatively high price[5], the SCI was an immediate success. By the late

[4]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.

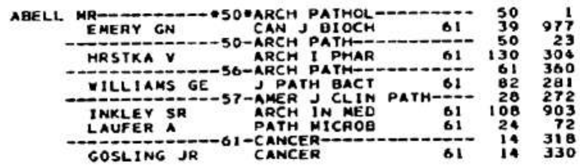
[5]The cost of the 1964 SCI was $1,950 (roughly $19,000 in 2023) for private sector firms, and $1,250 (roughly $12,000 in 2023) for university libraries (Pizer, 1964).

Figure 1: Entry in Science Citation Index

(a) The 1961 SCI volume

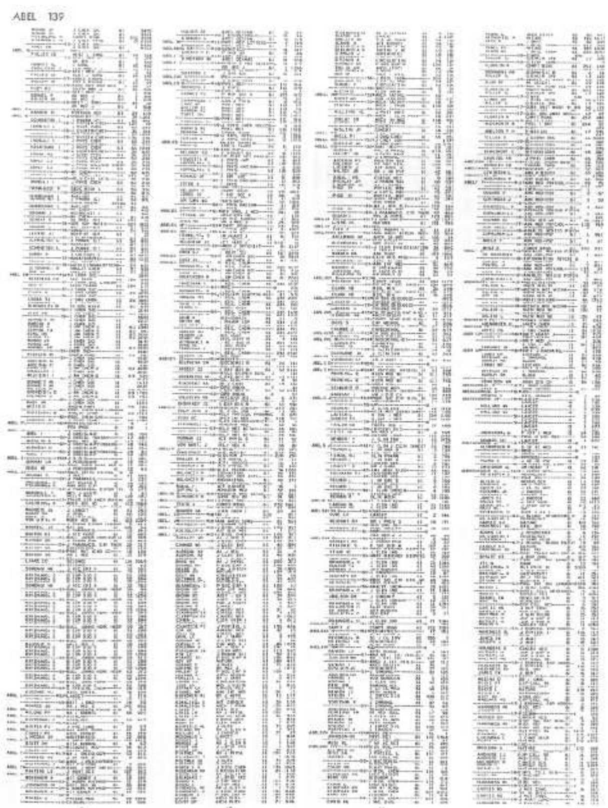


(b) An entry in the SCI



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

(c) A page in the SCI



Notes: Panel (a) shows the five books of the 1961 SCI. Panel (b) 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 articles. Because the example is from the 1961 volume of the SCI, all citations are from 1961. Panel (c) shows a sample page in the 1961 volume of the SCI.

1960s, every major university had a subscription. 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 Appendix Figure A.2).[6]

2.2 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 in the SCI. This means that only an incomplete set of citations was visible at the time. Both citations from before the SCI was introduced in 1961, as well as citations in journals that were not indexed by the SCI, remained invisible. In the 1970s and 1980s, the SCI was backward expanded to cover additional years and journals, and later became part of the *Web of Science*. As a result, the *Web of Science* contains both citations that were visible to contemporaries and citations that became available during the backward expansions and were thus invisible to contemporaries.

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*. Appendix Figure A.1 shows a sample journal list. Using this linking procedure, we can identify which citations were part of the information set of the 1960s, and crucially, which ones were not.

Faculty Rosters

To study how the introduction of citation metrics affected 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 et al., 2022). The data contain almost comprehensive cross-sections of all U.S. 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 medicine, biology, biochemistry, chemistry,

[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 from citing journals between 1965 and 1969 (Garfield, 1971).

physics, or mathematics. For the period of our analysis, the database provides the most comprehensive data on academics in the United States (see Iaria et al. (2022) for details). For the 1969 cross-section, the data contain 26,404 scientists (in the six fields) at 1,443 departments in 378 universities (Table 1, Panel B).

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. This allows us to observe academics who published and received citations, but also academics who did not publish or who did not receive any citations. This enables us to construct comprehensive individual and department rankings based on *all* academics and not only on those who published and were cited.

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 et al. (2022). The links are based on the academic's surname, first name or initials (depending on whether first names are available), country, city, and subject. The matching is based on the primary subject of each academic (e.g., physics) to reduce the number of false positives. To harmonize affiliations across the faculty rosters and the *Web of Science*, we rely on *Google Maps API*.

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. Crucially 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 captured in the SCI and were thus visible to contemporaries.

The average scientist in our data published 8.81 papers between 1956 and 1969 (Table 1, Panel A). These papers received 109 citations that were visible to contemporaries and 49 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

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

data received more than 9,000 visible and more than 3,900 invisible citations between 1956 and 1969.

Table 1: Descriptive Statistics

Panel A: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Publications	8.81	16.77	0	405
Visible Citations	109.43	310.92	0	9,064
Invisible Citations	48.65	147.48	0	3,904
Full Professor Share	0.38			
Female Share	0.10			

Panel B: Number of Observations

Dataset includes:	Observations
Citations	4,173,968
Publications	232,666
Scientists	26,404
Departments	1,443
Universities	378

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, i.e., their papers published before being observed in the 1969 cross-section; visible citations is the number of citations these papers received between 1956 and 1969 that were visible in the SCI; and invisible citations is 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 scientist, publication, citation, university, and department levels.

Constructing Scientist Rankings

Based on our scientist-publication-citation-linked data, we can construct rankings based on citations and publications. Within each 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). 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 mathematician received six citations, while the median medical researcher received 55 citations. If percentiles cannot be uniquely assigned because too many scientists have the same number of citations or publications, we assign the mid-point of the percentiles.

Constructing Department Rankings

Our data also allow us to construct the most comprehensive department rankings for this time period. Importantly, these are the first rankings for this period that are based on scientific output (as opposed to reputation-based 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 1,443 departments in 378 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, i.e., the average citation count of scientist i's colleagues. We then assign the rank based on the percentile in the subject-specific distribution of leave-out mean citation counts. We use the percentile rank because it allows us to compare the relative position of departments in the separate distributions for different scientific subjects (physics, chemistry, and so on); all with different numbers of departments and scientists.

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 the number of publications. That is, we construct a department's rank based on the average number of publications and the leave-out mean of publications. Second, we construct department percentile ranks based on data from Roose and Andersen (1970), and Cartter (1966), which provide reputation-based rankings for various subjects. As highlighted above, these rankings cover far fewer universities. The Cartter-ranking contains 106 universities (Cartter, 1966), and the Roose-Andersen ranking contains 130 (Roose and Andersen, 1970), while our baseline ranking contains 378 universities.[8] In Appendix B.2., we list the top 20 departments in each of the academic subjects, as

[8]These alternative rankings strongly correlate with our main citation-based ranking. The correlation between the Roose-Andersen ranking and our citation-based ranking is 0.67, while the correlation between the Cartter ranking and our citation-based ranking is 0.65.

measured by the various rankings. Our main analysis is robust to using either one of these department rankings.

2.3 How Was the SCI Used in Hiring and Promotions?

While the SCI was predominately 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:

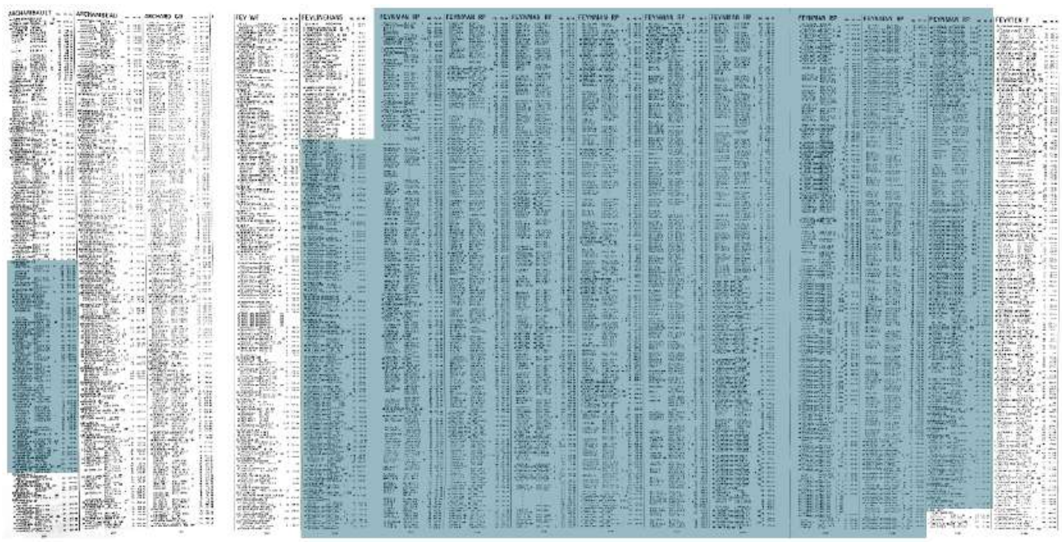
> "is intended as an aid to tracking down the literature on a given topic. University appointments committees have picked up the habit of using it as a rough and ready (too rough and ready) way of comparing the scientific achievements of applicants for jobs." (Dawkins, 1986, p. 427)

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 different scientists. Figure 2 shows one such comparison for two scientists working at the California Institute of Technology. The box on the left shows citations of the physicist Charles B. Archambeau. The box on the right shows the citations of the 1965 physics Nobel Laureate Richard P. 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 applicants' portfolios (Wade, 1975, p. 429). The importance of newly available citation metrics is also exemplified in the court case *Johnson v. University of Pittsburgh*[9]. In 1973, Sharon 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.

[9] *Dr. Sharon Johnson v. The University of Pittsburgh*, W.Da. PA., 1977.

Figure 2: Comparison of SCI Entries



Notes: This figure compares the entries in the 1965-1969 cumulation of the SCI (Garfield, 1971) for two physicists at the California Institute of Technology: Charles B. Archambeau on the left, and Nobel laureate Richard P. Feynman on the right.

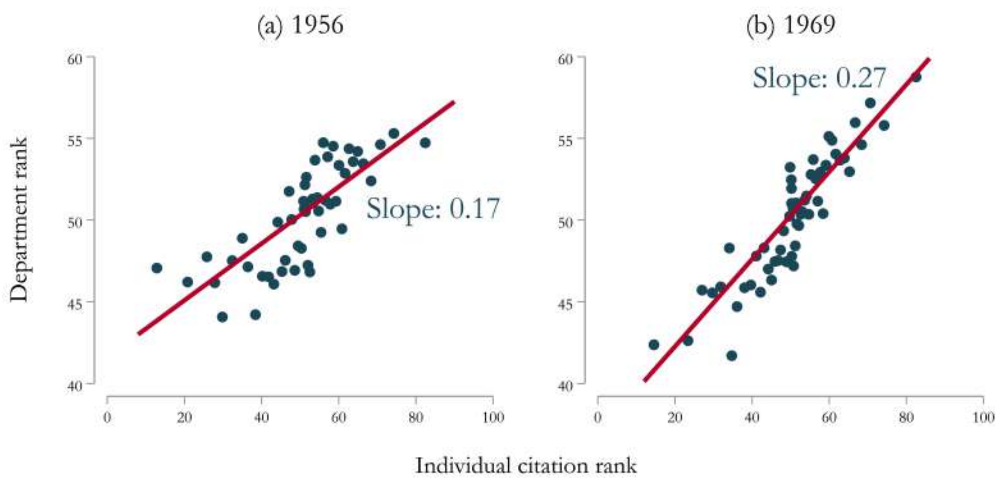
The SCI's Impact on Assortative Matching: Suggestive Evidence

To motivate our empirical strategy, we provide suggestive evidence of the impact of the SCI on the assortative matching of academics to 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 should increase after the publication of the SCI. We investigate this hypothesis by drawing binscatter plots showing the relationship between the individual citation rank and the department rank (Figure 3). We find that the correlation between a scientist's individual citation rank and their department rank increased by 54% (Figure 3, panels (a) and (b)) between 1956 and 1969. At the same time, the correlation between the individual publication rank and the department rank decreased by 36% (Figure 3 panels (c) and (d)).

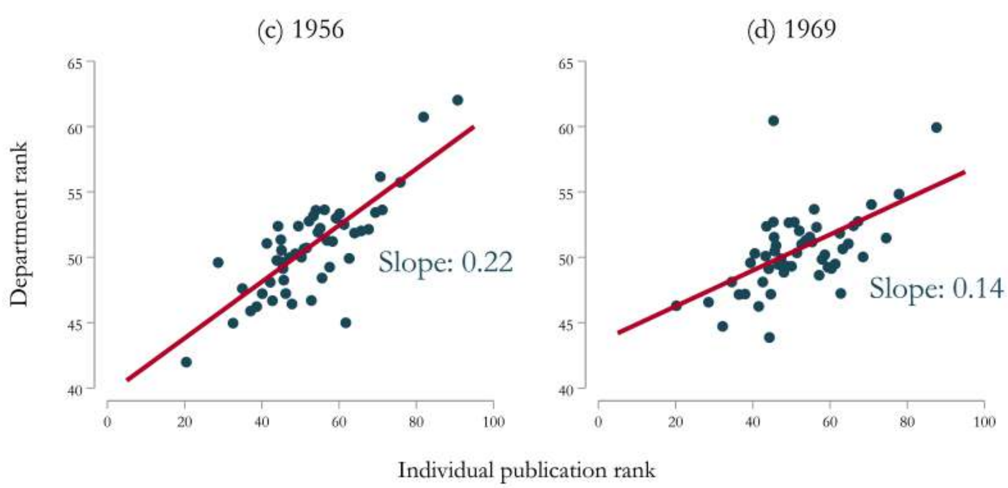
The evidence in this figure is in line with the hypothesis that the introduction of citation metrics increased the reliance of hiring decisions on citations, and decreased the reliance on other observable characteristics such as publications. However, the increasing correlation between scientists' citation 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 disproportionately favor leading departments and allow them to attract scientists, who turn out to be highly

Figure 3: Assortative Matching Before and After Citation Metrics

Assortative Matching by Citations



Assortative Matching by Publications



Notes: Panels (a) and (b) show the conditional correlation of individual scientists' citation rank and their department rank for two cross-sections: 1956 and 1969. Panel (a) shows a binned scatter plot for 1956 and thus before the introduction of the SCI. While we can now measure these citations in the *Web of Science*, they were not observable at the time. Panel (b) shows a binned scatter plot for 1969 and thus after the introduction of the SCI. The regression coefficient in both panels is conditional on an individual's publication rank. Panels (c) and (d) show the conditional correlation between individual 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.

cited. Similarly, increases in team production (e.g., Wuchty et al., 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.

3 The Effect of Citation Metrics on Assortative Matching

3.1 Empirical Strategy

We identify the causal effect of measuring citations 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 cit*ing* 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 cit*ed* 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 contained citations from 1961 in any of 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. Because of limited computing power, the collection of citation data was interrupted in 1962 and 1963. By 1964, data collection resumed. The set of covered citing journals quickly expanded from 613 in 1961 to more than 2,000 in 1969. As a 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.

Our data allow us to measure the citations that were visible in the SCI and also to measure citations that were invisible to contemporaries. Invisible citations can be measured today because citation databases were expanded to include citing articles for additional years and for a larger set of citing journals. Thus, we reconstruct the information set of scientists in the 1960s, and crucially we can also infer which citations were not part of that information set. Using this approach, we construct a separate count of visible and invisible citations for each scientist.

Table 2 illustrates the identifying variation for a hypothetical scientist. It reports citations to the scientist's papers, which can be 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 citations from Journal C were not covered in the 1960s. The shaded cells indicate citations that were visible to contemporaries because the SCI collected citations for those years and citing journals. The white cells indicate citations that were invisible because the SCI did not collect data for those years and citing journals. In other words, citations in shaded cells were part of contemporaries' information set, while citations in white cells were not.

Table 2: Illustration of The Identifying Variation

	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 shaded cells indicate citations that were visible in the SCI because the citation occurred in a journal and in a year (1961, or 1964-69) that was covered by the SCI. Numbers in white cells indicate citations that were invisible in the SCI, but are observable today.

In the example, the hypothetical scientists' 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 covered in our study period, all of these citations were invisible to contemporaries.

Hence, if contemporaries in 1969 had looked up the scientist's total citations in the SCI, they would have found six citations. Hence, the scientist's *visible* citation count is six. The scientist received eight additional citations, but these were *invisible* at the time. Yet, modern citation data allow us to observe these 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.

Our identification strategy then exploits the differential visibility of individual 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.[10] 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 timing or the quality of the citing journals, i.e., by the two sources of variation in the visibility of citations. We will address these concerns in a series of robustness checks outlined below.

The identification strategy gives rise to the following regression equation:

$$\begin{aligned} \textit{Dep. Rank}_i = {} & \delta \cdot Visible\,Citations_i + \theta \cdot Invisible\,Citations_i \\ & + \pi \cdot Publications_i + Subject\,FE + \epsilon_i \end{aligned} \tag{1}$$

where $\textit{Dep. Rank}_i$ is the department rank of scientist i in 1969.[11] $Visible\,Citations_i$

[10] Invisible citations may still correlate with outcomes, because scientists have always had a rough idea of the quality, and thus citation potential, of their peers' papers.

[11] In the main specification, we use the department ranking based on the leave-out mean of citations. As we show in Table C.1, all results are robust to different measures of the department rank, e.g., based on citations, based on publications, or alternative department rankings based on contemporaneous reputation-based surveys.

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.[12] $Publications_i$ flexibly control for scientists 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.

Crucially, we compare the magnitudes of the coefficients δ and θ. If the visibility of citations in the SCI increased the assortativeness of the match between scientists and departments, we would expect the coefficient δ to be larger than θ. For example, the difference between δ and θ captures if citations that occurred in 1961 instead of 1962 have a larger impact on the match between scientists and departments. Note that we would not expect θ to be zero as even in the absence of the SCI scientists will have an approximate idea about the importance and quality of other scientists' papers (an idea supported by the positive correlation in Figure 3, Panel (a)).

3.2 Main Results

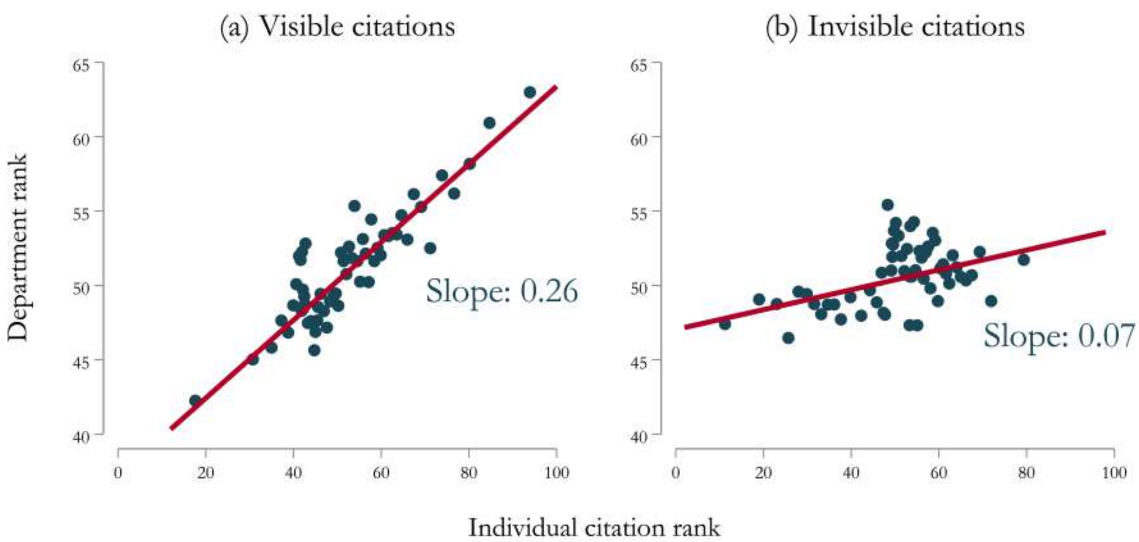
We illustrate the main regression in Figure 4. The figure shows binscatter plots for the relationship between visible and invisible citations and the department rank of an academic. In line with our hypothesis, academics are significantly more sorted based on visible than on invisible citations.

We report estimates of Equation (1) in Table 3. In column (1), we report a specification that controls for subject-fixed effects. The coefficient for visible citations is around two and a half times larger than the coefficient for invisible citations. Scientists with a 10 percentile higher visible citation count were, on average, placed at a 2.8 percentiles higher-ranked department in 1969. For example, a chemist would be placed at Harvard or Berkeley as opposed to the University of Illinois Urbana-Champaign or Michigan. In contrast, scientists with a 10 percentile higher invisible citation count were on average only placed at a 1.1 percentiles higher-ranked department.[13] 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%-level.

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

[13] As discussed above, it is not surprising that even invisible citations positively affect placements because they proxy for wider recognition by the scientific community.

Figure 4: Predictiveness of Visible and Invisible Citations



Notes: Panels (a) and (b) show the predictiveness of visible and invisible citations on the match between scientists and departments. Panel (a) shows a binned scatter plot with the visible citation percentile rank on the horizontal axis and the department rank on the vertical axis, conditional on invisible citations and publication controls. Panel (b) shows a binned scatter plot with the invisible citation percentile rank on the horizontal axis and the department rank on the vertical axis, conditional on visible citations and publication controls. The plotted relationships correspond to column (3) in Table 3. The slopes are significantly different from each other; the p-value from a t-test of no difference is < 0.001 (see also column (3) in Table 3).

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). In column (2), we show that the results are robust to controlling for the number of publications by year, i.e., controlling separately for the number of publications in 1956, 1957, and so on.[14]

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)).

[14]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.

Table 3: The Effect of Visible and Invisible Citations on Assortative Matching

	Dependent variable: Department rank				
	(1)	(2)	(3)	(4)	(5)
Rank Visible Citations	0.282***	0.300***	0.262***	0.232***	0.227***
	(0.034)	(0.031)	(0.034)	(0.034)	(0.035)
Rank Invisible Citations	0.110***	0.076***	0.067***	0.061***	0.058**
	(0.023)	(0.020)	(0.021)	(0.023)	(0.024)
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
P-value (Rank Visible = Rank Invisible)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Observations	26,404	26,404	26,404	26,404	26,404
R^2	0.131	0.134	0.147	0.227	0.253

Notes: The table reports the estimates of Equation (1). The dependent variable is the department rank of scientist i in 1969, measured in percentiles. To construct the department rank, we calculate the leave-out mean of citations of all scientists in the department of scientist i. We then assign the rank based on the percentile in the distribution of leave-out mean citations. The first explanatory variable measures scientist i's individual rank in the distribution of visible citations (i.e., all citations that were visible in the SCI; see Section 3.1 for details). The second explanatory variable measures scientist i's individual rank in the distribution of *in*visible citations (i.e., all citations that were not visible in the SCI). Publications by Year separately measure the number of scientist i's publications in each year between 1956 and 1969. Publications by Journal separately measure the number of scientist i's publications in each journal (e.g., *Nature* or *Science*). Standard errors are clustered at the department level. Significance levels: $***$ p<0.01, $**$ p<0.05, and $*$ p<0.1.

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 1,714 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 very 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.

Taken together, the results indicate that the availability of citation metrics indeed led departments to select scientists based on the citations that were visible in the SCI. Importantly, the differential effect of visible and invisible citations cannot be explained by the differential timing of publications or the quality of journals in which the cited paper appeared. In the next part of the paper, we investigate this result further and rule out alternative explanations that might explain our findings.

3.3 Ruling out Alternative Explanations

Despite the somewhat arbitrary nature of the SCI coverage, our 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. This may occur for two main reasons. First, visible citations may come from citing articles in higher-quality journals and may, therefore, have a larger impact on assortative matching between scientists and departments. Second, as the SCI was introduced in 1961, visible citations are more likely to occur in later years, which may have had a larger impact on assortative matching in 1969. We address these concerns by exclusively relying on over-time or across-journal variation in the visibility of citations, thereby holding fixed the other source of variation.

Quality of Citing Journals

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

Nonetheless, we address the potential concern of differences in the quality of citing journals by fixing the set of journals from which citations are drawn. For this test, we only rely on over-time variation 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 from the set of journals that were included in the first edition of the SCI in 1961 (i.e., only using over-time variation in citations from type A journals in Table 2).[15]

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. We do not consider citations in type B or C journals, i.e., journals not indexed in the first SCI in 1961, for this test.

The results that use only citations from type A citing journals are almost identical to the main results (see Table 4). Not only are the point estimates very similar, but also the p-values for the difference in coefficients remain below the 0.1%-level. These results highlight that differences in the quality of citing journals do not drive our findings.

Table 4: Robustness Check: Citations From a Consistent Set of Journals

	Dependent variable: Department rank				
	(1)	(2)	(3)	(4)	(5)
Rank Visible Citations	0.274***	0.282***	0.243***	0.215***	0.208***
	(0.033)	(0.029)	(0.032)	(0.033)	(0.034)
Rank Invisible Citations	0.114***	0.080***	0.071***	0.069***	0.066***
	(0.022)	(0.019)	(0.020)	(0.022)	(0.023)
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
P-value (Rank Visible = Rank Invisible)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Observations	26,404	26,404	26,404	26,404	26,404
R^2	0.122	0.125	0.141	0.223	0.250

Notes: The table reports the estimates of Equation (1). To construct citation ranks, we only consider citations in journals that were covered by the 1961 edition of the SCI. The dependent variable is the department rank of scientist i in 1969, measured in percentiles. To construct the department rank, we calculate the leave-out mean of citations of all scientists in the department of scientist i. We then assign the rank based on the percentile in the distribution of leave-out mean citations. The first explanatory variable measures scientist i's individual rank in the distribution of visible citations in type A journals (see Table 2). The second explanatory variable measures scientist i's individual rank in the distribution of *in*visible citations in type A journals. Publications by Year separately measure the number of scientist i's publications in each year between 1956 and 1969. Publications by Journal separately measure the number of scientist i's publications in each journal (e.g., *Nature* or *Science*). Standard errors are clustered at the department level. Significance levels: $***$ p<0.01, $**$ p<0.05, and $*$ p<0.1.

[15]We visualize the underlying variation of this robustness check in panel (b) of Appendix Figure C.1.

The Timing of Citations

The timing of the introduction of the SCI was plausibly exogenous, i.e., there is no particular reason why the SCI was first published in 1961 instead of, say, 1960. However, because citations could only become visible after 1961, visible citations, on average, occurred in later years than invisible ones. If later citations had more predictive power for career outcomes in 1969, differences in the effect of visible and invisible citations may stem from the differential timing of citations.

Table 5: Robustness Check: Citations Only From Years With SCI

	Dependent variable: Department rank				
	(1)	(2)	(3)	(4)	(5)
Rank Visible Citations	0.314***	0.321***	0.280***	0.256***	0.247***
	(0.038)	(0.035)	(0.038)	(0.039)	(0.040)
Rank Invisible Citations	0.084***	0.061***	0.055***	0.038**	0.039***
	(0.017)	(0.014)	(0.015)	(0.015)	(0.015)
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
P-value (Rank Visible = Rank Invisible)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Observations	26,404	26,404	26,404	26,404	26,404
R^2	0.130	0.133	0.147	0.226	0.253

Notes: The table reports the estimates of Equation (1). To construct citation ranks, we only consider citations in years when the SCI was available (i.e., 1961, and 1964-1969). The dependent variable is the department rank of scientist i in 1969, measured in percentiles. To construct the department rank, we calculate the leave-out mean of citations of all scientists in the department of scientist i. We then assign the rank based on the percentile in the distribution of leave-out mean citations. The first explanatory variable measures scientist i's individual rank in the distribution of visible citations (i.e., all citations that were visible in the SCI; see Section 3.1 for details). The second explanatory variable measures scientist i's individual rank in the distribution of *in*visible citations (i.e., all citations that were not visible in the SCI). Publications by Year separately measure the number of scientist i's publications in each year between 1956 and 1969. Publications by Journal separately measure the number of scientist i's publications in each journal (e.g., *Nature* or *Science*). Standard errors are clustered at the department level. Significance levels: $***$ p<0.01, $**$ p<0.05, and $*$ p<0.1.

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.[16]

For our hypothetical scientist presented in Table 2, this test considers six visible citations: one from journal A in 1961 and 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.[17]

The results that use only citations from years in which the SCI was published are very similar to the main results (Table 5). The point estimates are almost identical, and the p-values for the difference in coefficients remain below the 0.1%-level. These results strongly suggest that the differential timing of visible and invisible citations does not drive our findings.

3.4 Placebo Test

We provide further evidence that citations in journals covered by the SCI only started to matter once the SCI became available. For this placebo test, we construct pseudo-visible citations. We define citations as pseudo-visible, if they come from citing journals that were included in the 1961 issue of the SCI (i.e., type A journals in Table 2) but occurred in years when the SCI was not available (i.e., in 1956-1960 and 1962-1963). We construct four citation ranks for each scientist:

1. Rank visible citations (SCI years): citations from journals that were covered in the SCI in years when the SCI was published (1961 and 1964-1969),

2. Rank invisible citations (SCI years): citations from journals that were not covered in the SCI in years when the SCI was published (1961 and 1964-1969),

3. Rank pseudo-visible citations (non-SCI years): citations from journals that were covered in the SCI in 1961 but from years when the SCI was not published (1956-1960 and 1962-1963),

4. Rank invisible citations (non-SCI years): citations from journals that were not covered in the SCI in 1961 and from years when the SCI was not published (1956-1960 and 1962-1963).

[16]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, 1963b, p. xvii). As a result, citations in many reputable journals remained invisible.

[17]See also panel (c) of Appendix Figure C.1.

For our hypothetical scientist presented in Table 2, this test considers six visible citations in SCI years: one from journal A in 1961 and two from journal A in 1967, plus three from journal B in 1966. It also considers three invisible citations in SCI years: one each from journal B in 1961 and 1965, and one from journal C in 1969. Furthermore, it considers two pseudo-visible citations from non-SCI years: one each from journal A in 1959 and 1963. Finally, it considers three invisible citations from non-SCI years: one each from journal B in 1957, and one each from journal C in 1959 and 1962.[18]

For each scientist, we count the number of citations in these four categories and construct their subject-specific percentile ranks. Using these measures, we estimate the following regression:

$$\begin{aligned} \textit{Dep. Rank}_i = {} & \delta_1 \cdot \textit{Visible Citations (SCI years)}_i \\ & + \theta_1 \cdot \textit{Invisible Citations (SCI years)}_i \\ & + \delta_2 \cdot \textit{Pseudo-Visible Citations (non-SCI years)}_i \\ & + \theta_2 \cdot \textit{Invisible Citations (non-SCI years)}_i \\ & + \pi \cdot \textit{Publications}_i + \textit{Subject FE} + \epsilon_i \end{aligned} \tag{2}$$

As pseudo-visible citations were not visible to contemporaries, we would expect them to matter similarly to the invisible ones, i.e., we would expect $\delta_1 \gg \delta_2 \approx \theta_1 \approx \theta_2$.[19]

[18] See also panel (d) of Appendix Figure C.1.

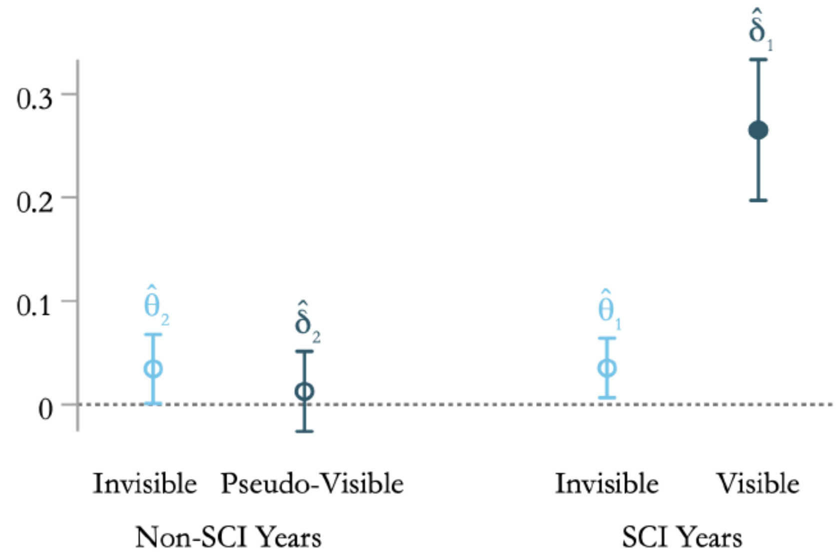
[19] Note that omitting the third and fourth term ($\textit{Pseudo-Visible Citations (non-SCI years)}_i$ and $\textit{Invisible Citations (non-SCI years)}_i$) from Equation (2) is equivalent to the robustness test presented in Table 5. In Table 6 we report regressions of this kind for reference (columns (1) and (2)).

Table 6: Placebo Test: Predictiveness of Citations Before the SCI

	Dependent variable: Department rank			
	Only SCI years		Incl. non-SCI years	
	(1)	(2)	(3)	(4)
Rank Visible Citations (SCI years)	0.280***	0.247***	0.265***	0.230***
	(0.038)	(0.040)	(0.035)	(0.036)
Rank Invisible Citations (SCI years)	0.055***	0.039***	0.035**	0.022
	(0.015)	(0.015)	(0.015)	(0.015)
Rank Pseudo-Visible Citations (non-SCI years)			0.012	0.027
			(0.020)	(0.022)
Rank Invisible Citations (non-SCI years)			0.034**	0.020
			(0.017)	(0.018)
Publications by Year × Subject	Yes	Yes	Yes	Yes
Publications by Journal × Subject		Yes		Yes
P-value (Visible = Invisible (SCI years))	< 0.001	< 0.001	< 0.001	< 0.001
P-value (Visible = Pseudo-Visible)			< 0.001	< 0.001
P-value (Invisible (SCI) = Invisible (non-SCI))			0.975	0.942
P-value (Pseudo-Visible = Invisible (non-SCI))			0.432	0.823
Observations	26,404	26,404	26,404	26,404
R^2	0.147	0.253	0.147	0.254

Notes: This table reports the estimates of Equation (2). The dependent variable is the department rank of scientist i in 1969, measured in percentiles. To construct the department rank, we calculate the leave-out mean of citations of all scientists in the department of scientist i. We then assign the rank based on the percentile in the distribution of leave-out mean citations. The first explanatory variable measures scientist i's individual rank in the distribution of visible citations in SCI years (i.e., all citations that were visible in the SCI; see Section 3.1 for details). The second explanatory variable measures scientist i's individual rank in the distribution of *in*visible citations in SCI years (i.e., all citations that were not visible in the SCI in 1961 and 1964-1969). The third explanatory variable measures scientist i's individual rank in the distribution of pseudo-visible citations in non-SCI years (i.e., all citations in journals that were contained in the SCI in 1961 but for years that were not covered in the SCI, i.e., 1956-1960 and 1962-1963). The fourth explanatory variable measures scientist i's individual rank in the distribution of *in*visible citations in non-SCI years (i.e., all citations in journals that were not contained in the SCI in 1961 and in years that were not covered, i.e., 1956-1960 and 1962-1963). Publications by Year separately measure the number of scientist i's publications in each year between 1956 and 1969. Publications by Journal separately measure the number of scientist i's publications in each journal (e.g., *Nature* or *Science*). Standard errors are clustered at the department level. Significance levels: $***$ p<0.01, $**$ p<0.05, and $*$ p<0.1. P-value from test $\theta_1 = \theta_2 = \delta_2$: 0.650 in column (3), 0.974 in column (4).

Figure 5: Plot of Coefficients from Placebo Test



Notes: The figure plots regression coefficients and corresponding 95 percent confidence intervals from Equation (2). The estimates correspond to column (3) in Table 6.

We find that the coefficient on visible citations from SCI years is almost identical to the baseline specification (Table 6). Strikingly, the coefficient on pseudo-visible citations from non-SCI years is a lot smaller and very similar to the coefficients on invisible citations. This indicates that citations in journals that were covered 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 pseudo-visible citations (p-value of test $\theta_1 = \theta_2 = \delta_2$: 0.650). Figure 5 visualizes the results of this placebo test.

3.5 Further Robustness Checks

In additional results, we show that the findings are robust to using alternative ways of ranking departments, using alternative transformations of individual citation counts, and to imposing additional sample restrictions.

Alternative Department Rankings

First, we consider alternative department rankings. The main results use department ranks based on the leave-out mean of citations. The results are robust to using rankings based on the mean of citations, i.e., including citations of the focal scientist (Table C.1, Panel A, column (2)). Instead of using department rankings based on citations, we can use scientists' publication counts to construct department rankings. This leaves the results almost unchanged (Table C.1, Panel A, columns (3) and (4)). Instead of percentile ranks, we can also use an indicator for being in a top five department in each subject. For example, the top five departments in mathematics are Princeton, Virginia Polytechnic Institute, Stanford, Chicago, and IAS Princeton. In line with our main results, a ten-percentile increase in visible citations increased the probability of being affiliated with a top-five department by 0.26 percentage points (i.e., a 12.7 percent increase). In contrast, invisible citations did not matter significantly (Table C.1, Panel A, column (5)).

Our results also hold if we construct department rankings based on the scientific output of departments in the 1956 cross-section (Table C.1, Panel B). While 1956 rankings have the advantage that they are determined before the introduction of the SCI, they are not available for universities that only enter the data after 1956. Moreover, the 1956 rankings may suffer from higher measurement error, because we measure department composition before hiring and moving decisions were actually made. Ranking departments on the basis of 1956 rankings results in a 25 percent smaller sample. Nevertheless, the results remain qualitatively unchanged.

Our results are also robust to using external department rankings that do not rely on citation or publication data. We draw on subject-specific reputational rankings from Roose and Andersen (1970) and Cartter (1966), to construct analogous department percentile ranks. As these rankings do not cover medical schools, we supplement these rankings with the first comprehensive ranking of medical schools by Cole and Lipton (1977). To avoid unnecessary sample selection for this robustness check, we assign departments that are unranked in these rankings to the average rank between 1 and the lowest-ranked department.[20] We report the results of these tests in Table C.2. The estimates show that our results are very similar if we use independently compiled reputation-based rankings.

[20] This is necessary, because these external rankings cover fewer departments than our data. Roose and Andersen (1970) and Cartter (1966) do not contain rankings for biology as a whole but for specific subfields of biology (Botany, Developmental Biology, Entomology, Microbiology, Molecular Biology, Physiology, Population Biology, and Zoology in the Roose-Andersen ranking; Botany, Entomology, Microbiology, Physiology, and Zoology in the Cartter ranking). Based on these rankings, we construct an overall ranking for biology by calculating the average rank of a department in the subfields of biology.

Alternative Transformations of Citation Counts

Second, we consider alternative ways of measuring scientists' performance. We show that the results are qualitatively similar if we use standardized citations instead of percentiles (Table C.3, column (2)). For this test, we standardize visible and invisible citations at the subject-level. As standardized citations contain large outliers, we show that the results are also robust to winsorizing at the 99th percentile and then standardizing citation counts (Table C.3, column (3)). Further, the results are also similar if we use the inverse hyperbolic sine transformation of citations (Table C.3, column (4)).

Another concern could be that the results are driven by differences in the distributions of visible and invisible citations. Potentially, larger measurement error for invisible citations could explain the smaller and insignificant coefficient for invisible citations. We address this concern with a robustness check in which we only use citations from 1956 to 1965 to construct visible and invisible citation ranks. This leads to very similar distributions of visible and invisible citations.[21] For these alternative variables, measurement error concerns would, if anything, disproportionately downward bias the coefficient on visible citations. Using these alternative individual citation ranks leaves our results qualitatively unchanged (Table C.3, column (5)).

Alternative Sample Restrictions

Third, we show that the results are robust to restricting the sample in various ways. In particular, the findings are robust to excluding scientists with zero citations from the sample (Table C.4, column (2)). This test shows that our findings are not driven by scientists without citations. We also show that the results are robust to excluding scientists in small departments because department ranks may be less precisely calculated in small departments. For this test, we restrict the sample to all scientists in departments with more than 10 scientists (Table C.4, column (3)).

3.6 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

[21]For citations measured in 1956-1965 the summary statstics are as follows. Visible citations: mean 32.4, standard deviation 97.0; invisible citations: mean 43.5, standard deviation 133.3.

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.[22] We then check whether these scientists remain active until 1969. We estimate the following regression:

$$\begin{aligned} \mathbb{1}[\mathit{Leaving\ Academia}]_i = \delta \cdot \mathit{Visible\,Citations}_i + \theta \cdot \mathit{Invisible\,Citations}_i \\ + \pi \cdot \mathit{Publications}_i + \mathit{Subject\,FE} + \epsilon_i \end{aligned} \quad (3)$$

where $\mathbb{1}[\mathit{Leaving\ Academia}]_i$ is an indicator variable that equals 1 if a scientist left academia between 1956 and 1969. The remaining variable definitions are identical to the definitions of Equation (1). Note that these regressions can only be estimated for the subsample of scientists we observe in 1956 and 1969.

The probability of leaving academia was lower for academics with a higher visible citation count (Panel A of Table 7). Scientists with a 10 percentile higher visible citation count were around 2.9 percentage points (or 4.2 percent relative to 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 difference in coefficients on visible and invisible citations are below 0.01. These findings suggest that the increased assortative matching of academics was, in part, driven by scientists with fewer visible citations leaving academia.

Effect on Moving to Higher-Ranked Department

As a second mechanism for increased assortative matching, we investigate the moves of scientists between departments. More specifically, we estimate a version of Equation (3) 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.

The probability that a scientist moved to a higher-ranked department increased with a higher visible citation rank (Panel B of Table 7). Scientists with a 10 percentile higher

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

Table 7: Mechanisms

	Dependent variable: Indicator for Career Outcome				
	(1)	(2)	(3)	(4)	(5)
Panel A: Dependent variable: Left academia between 1956 and 1969					
Rank Citations Visible	-0.0031***	-0.0032***	-0.0029***	-0.0025***	-0.0025***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Rank Citations Invisible	-0.0004	-0.0002	0.0001	0.0002	0.0003
	(0.0006)	(0.0005)	(0.0006)	(0.0006)	(0.0006)
P-value (Rank Visible = Rank Invisible)	0.005	0.002	0.002	0.008	0.009
Observations	11,625	11,625	11,625	11,625	11,625
R^2	0.078	0.083	0.104	0.219	0.262
Panel B: Dependent variable: Moved to higher-ranked department between 1956 and 1969					
Rank Visible Citations	0.0009***	0.0007***	0.0006**	0.0004	0.0005
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Rank Invisible Citations	-0.0003	-0.0002	-0.0002	-0.0003	-0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
P-value (Rank Visible = Rank Invisible)	0.017	0.087	0.124	0.226	0.294
Observations	6,154	6,154	6,154	6,154	6,154
R^2	0.009	0.013	0.030	0.307	0.363
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

Notes: This table reports the estimates of Equation (3). Panel A reports results from regressions with an indicator equal to one if scientist i was observed in the 1956 cross-section, but not in the 1969 cross-section, i.e., if i has left academia, as the dependent variable. These regressions use the 1956 cross-section of scientists who were not full professors in 1956. Panel B reports results from regressions with an indicator equal to one if scientist i moved to a higher-ranked department between 1956 and 1969, as the dependent variable. These regressions use the sample of scientists who are observed in both the 1956 and 1969 cross-sections of scientists. In both panels, the first explanatory variable measures scientist i's rank in the distribution of visible citations (i.e., all citations that were visible in the SCI; see Section 3.1 for details). The second explanatory variable measures scientist i's rank in the distribution of *in*visible citations (i.e., all citations that were not visible in the SCI). Publications by Year separately measure the number of scientist i's publications in each year between 1942 and 1969. Publications by Journal separately measure the number of scientist i's publications in each journal (e.g., *Nature* or *Science*). Standard errors are clustered at the 1956-department-level in Panel A, and at the 1969-department-level in Panel B. Significance levels: $***$ p<0.01, $**$ p<0.05, and $*$ p<0.1.

visible citation count were around 0.6 percentage points more likely to move to a higher-ranked department. This relatively small point estimate nevertheless represents an 11.6 percent increase relative to the mean. Invisible citations did not affect the probability of moving to a higher-ranked department. The results are robust to controlling for publications by year but turn insignificant if we add thousands of variables that control for publications by journal and publications by journal and subject. Overall, the results suggest that assortative matching also increased because scientists with many visible citations moved to higher-ranked departments.

4 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.

4.1 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 non-parametric version of our main regression:

$$\begin{aligned} Dep.\ Rank_i = &\sum_q \delta_q \cdot \mathbb{1}(Visible\ Cit\ Decile_i = q) \\ &+ \sum_q \theta_q \cdot \mathbb{1}(Invisible\ Cit\ Decile_i = q) \\ &+ \pi \cdot Publications_i + Subject\ FE + \epsilon_i \end{aligned} \tag{4}$$

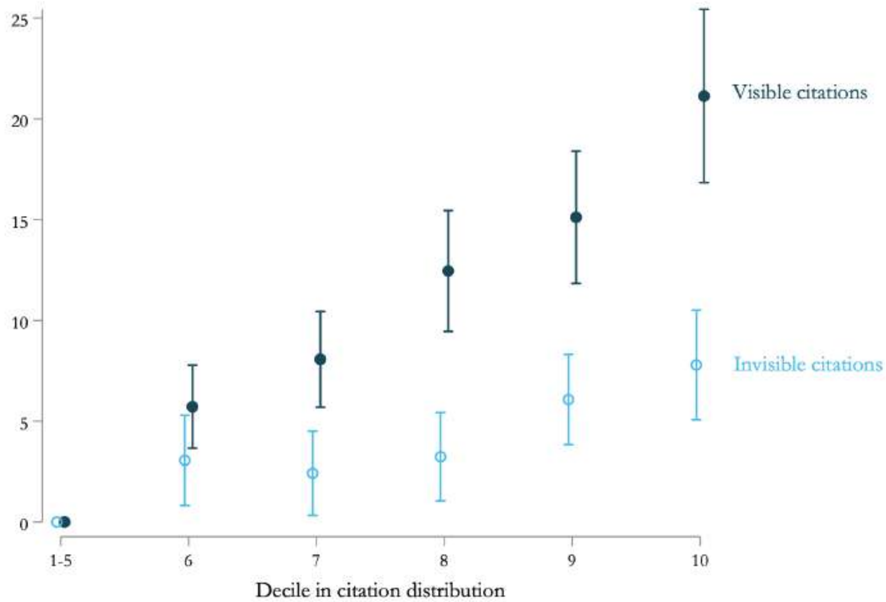
$\mathbb{1}(Visible\ Cit\ Decile_i = q)$ and $\mathbb{1}(Invisible\ Cit\ Decile_i = q)$ are indicator variables for i's decile in the visible and invisible citation distributions, respectively.[23] We visualize the estimates relative to the bottom half of the visible and invisible individual-level citation distribution (Figure 6).[24]

Over the upper half of the citation distribution, an increase in visible citations increases the rank of a scientist's 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 21.1 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

[23] To save space, we report results for the specification that separately controls for the number of publications by year and subject (equivalent to column (3) in Table 3). The results for the other specifications are almost identical.

[24] 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.

Figure 6: Heterogenous Effects by Individual-Level Citation Rank



Notes: The figure plots estimated regression coefficients δ_q (visible citations, dark blue) and θ_q (invisible citations, light blue) and corresponding 95 percent confidence intervals from Equation (4).

placed at Harvard as opposed to Florida State 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 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.

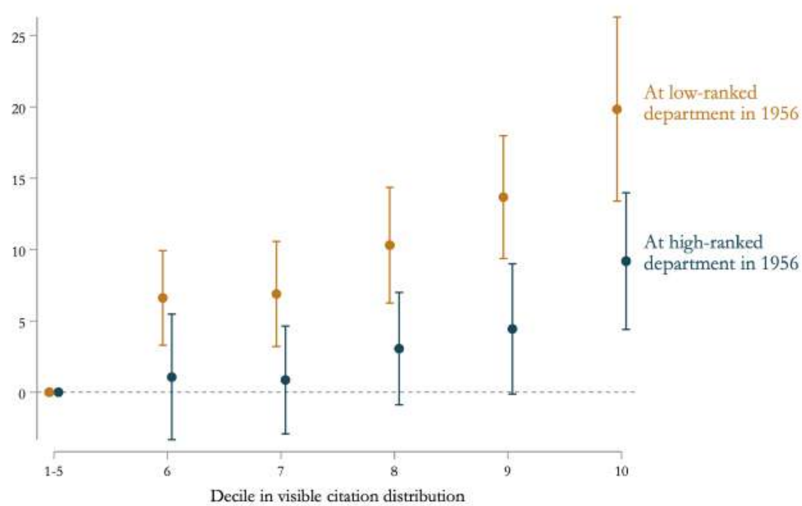
4.2 Heterogeneous Effects for Peripheral Scientists

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

$$
\begin{aligned}
Dep.\ Rank_i = & \sum_q \delta_q^H \cdot \mathbb{1}(Visible\,Cit\,Decile_i = q) \times High\text{-}Ranked\ (1956)_i \\
& + \sum_q \delta_q^L \cdot \mathbb{1}(Visible\,Cit\,Decile_i = q) \times Low\text{-}Ranked\ (1956)_i \\
& + \sum_q \theta_q^H \cdot \mathbb{1}(Invisible\,Cit\,Decile_i = q) \times High\text{-}Ranked\ (1956)_i \\
& + \sum_q \theta_q^L \cdot \mathbb{1}(Invisible\,Cit\,Decile_i = q) \times Low\text{-}Ranked\ (1956)_i \\
& + \omega \cdot Low\text{-}Ranked\ (1956)_i + \pi \cdot Publications_i + Subject\ FE + \epsilon_i
\end{aligned} \tag{5}
$$

Variable definitions are identical to Equation (4). In addition, 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 define low-ranked departments as those below the 75th percentile of the department ranking.[25]

Figure 7: Heterogenous Effect of Citation Rank for Peripheral Scientists



Notes: The figure plots estimated regression coefficients δ_q^H and δ_q^L and 95 percent confidence intervals from Equation (5). I.e., it plots separate sets of coefficients for scientists who were based in high-ranked (blue) and low-ranked (brown) departments in the 1956 cross-section. We define low-ranked departments as those below the 75th percentile of the department ranking in 1956. In physics, for example, low-ranked departments are all departments that were ranked lower than the University of Wisconsin, Madison.

[25]Results are qualitatively similar if we use alternative cutoffs (e.g., 60th, 70th, 80th, or 90th percentile, see Appendix Figure D.3).

We show estimates for the deciles of the visible citation distribution for scientists in high-ranked and low-ranked departments in Figure 7.[26] Estimates for scientists in low-ranked departments are consistently larger than for scientists in high-ranked departments. This suggests that scientists who were in lower-ranked departments in 1956 benefited disproportionately from the availability of citation metrics.[27]

In other words, citation metrics allowed 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 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)

4.3 Heterogeneous Effects for Minorities

In the last part of this section, we investigate heterogeneous impacts of the SCI on minorities. Specifically, we analyze whether women, Hispanics, Asians, and Jews disproportionately benefited from the availability of citation metrics. We identify these groups based on the names of academics (for more details, see Appendix B.1.). We then estimate the following regression:

$$\begin{aligned} Dep.\ Rank_i = & \sum_q \delta_q^M \cdot \mathbb{1}(Visible\,Cit\,Decile_i = q) \times Majority_i \\ & + \sum_q \delta_q^m \cdot \mathbb{1}(Visible\,Cit\,Decile_i = q) \times Minority_i \\ & + \sum_q \theta_q^M \cdot \mathbb{1}(Invisible\,Cit\,Decile_i = q) \times Majority_i \\ & + \sum_q \theta_q^m \cdot \mathbb{1}(Invisible\,Cit\,Decile_i = q) \times Minority_i \\ & + \omega \cdot Minority_i + \pi \cdot Publications_i + Subject\,FE + \epsilon_i \end{aligned} \tag{6}$$

Variables are defined as before, but we add indicator variables that equal one if the academic belongs either to the majority or to the minority. Overall, we do not find systematic evidence that minorities benefited more or less from the availability of citation metrics (Figure 8). The confidence intervals for all estimates overlap. Not surprisingly,

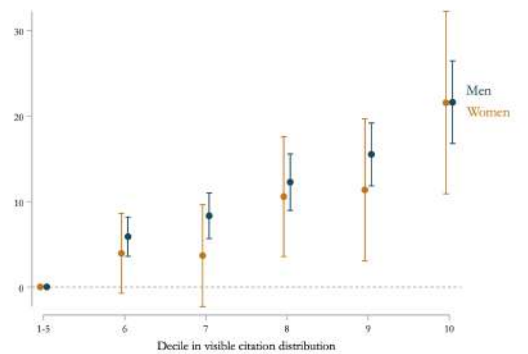
[26] To improve clarity, the figure does not report the estimates for the invisible citation deciles. As in Figure 6, the estimates for invisible citations are consistently smaller than for visible citations. We also find no difference in the impact of invisible citations depending on the department rank.

[27] These results may be interpreted as mechanical because scientists working in low-ranked departments in 1956 have more scope to move to a higher-ranked department. However, showing such effects is relevant for evaluating the distributional impact of citation metrics.

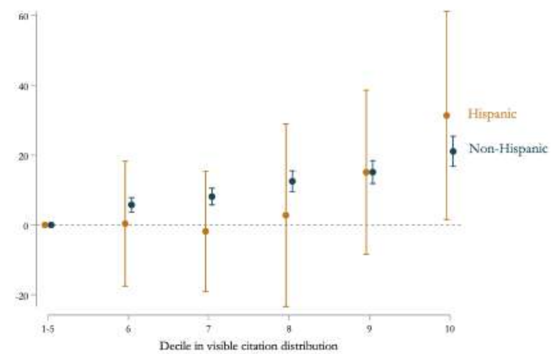
some estimates are relatively noisy because minority groups, by definition, comprise relatively few observations in 1969 (see e.g., Iaria et al. (2022)). Overall, these results suggest that the availability of more "objective" performance metrics did not help minorities overcome potential discrimination in the hiring process. However, the results also highlight that the use of performance metrics did not widen discrimination against minority groups.

Figure 8: Heterogenous Effects for Minority Scientists

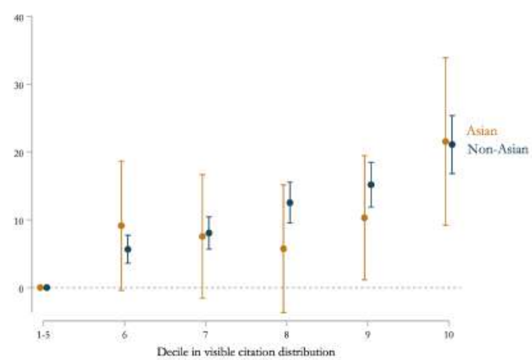
(a) Female Academics



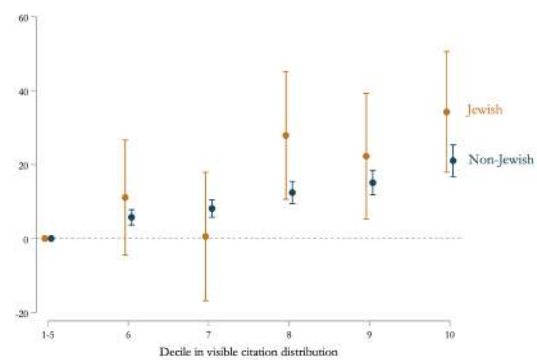
(b) Academics with Hispanic Names



(c) Academics with Asian Names



(d) Academics with Jewish Names



Notes: The four panels plot estimated regression coefficients δ_q^M (blue) and δ_q^m (brown), and corresponding 95 percent confidence intervals from Equation (6). Panel (a) plots separate sets of coefficients for women (brown) and men (blue). Panel (b) plots separate sets of coefficients for Hispanics (brown) and Non-Hispanics (blue). Panel (c) plots separate sets of coefficients for Asians (brown) and Non-Asians (blue). Panel (d) plots separate sets of coefficients for Jews (brown) and Non-Jews (blue).

5 Impact of Performance Metrics on Promotions

In the last part of the paper, we investigate the impact of citation metrics on promotions. In particular, we investigate if scientists who 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. We estimate the following regression:

$$\begin{aligned}\mathbb{1}[Promoted\ Full\ Prof.]_i = {} & \delta \cdot Visible\ Citations_i + \theta \cdot Invisible\ Citations_i \\ & + \pi \cdot Publications_i + Subject\ FE + \epsilon_i\end{aligned} \tag{7}$$

where $\mathbb{1}[Promoted\ Full\ Prof.]_i$ is an indicator that equals one if scientist i was promoted to full professor between 1956 and 1969. The remaining variable definitions are identical to Equation (1). The coefficients of δ and θ measure how much the probability of promotion changes for scientists with more visible and invisible citations, respectively.

The visible citation rank has a significant positive impact on the probability of promotion (Table 8). The probability of promotion increased by 4.5 percentage points (or 6.3 percent relative to the mean) for scientists with a 10 percentile higher visible citation rank.[28] The estimates for invisible citations are very close to zero and statistically insignificant. We also report the p-value of a two-sided t-test for the equality of the two citation coefficients. We reject equality of the two coefficients with a p-value below 0.1 for four of the five specifications. Because of the small sample size and the demanding specification with a very large number of control variables for the number of publications by journal and subject (e.g., the number of publications in *Nature* for physicists, the number of publications in *Nature* for chemists, the number of publications in *Science* for physicists, and so on), the coefficients are not statistically significantly different from each other for the specification reported in column (5). Nevertheless, the qualitative difference between visible and invisible citations remains unchanged.

As in the analysis of assortative matching (Section 3), we rule out potential alternative explanations. We show that these results are robust to restricting citations only to the set of journals that were covered in the first SCI, i.e., the 1961 SCI. This holds fixed the quality of the citing journals and exploits only over-time variation in citation

[28] The effect of citation metrics on promotions is estimated within the set of academics who we observe in 1956 and who have not left academia by 1969. Since the probability of leaving academia decreases with visible citations (see Section 3.6), we likely estimate a lower-bound of the effect of citation metrics on promotions.

Table 8: The Effect of Visible and Invisible Citations on Promotions

	Dependent variable: Promoted to Full Professor				
	(1)	(2)	(3)	(4)	(5)
Rank Visible Citations	0.0040***	0.0044***	0.0045***	0.0037***	0.0036**
	(0.0007)	(0.0008)	(0.0008)	(0.0013)	(0.0016)
Rank Invisible Citations	0.0010*	0.0004	0.0006	0.0000	0.0000
	(0.0006)	(0.0007)	(0.0007)	(0.0011)	(0.0014)
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
P-value (Rank Visible = Rank Invisible)	0.016	0.002	0.003	0.086	0.195
Observations	2,906	2,906	2,906	2,906	2,906
R^2	0.142	0.149	0.159	0.394	0.422

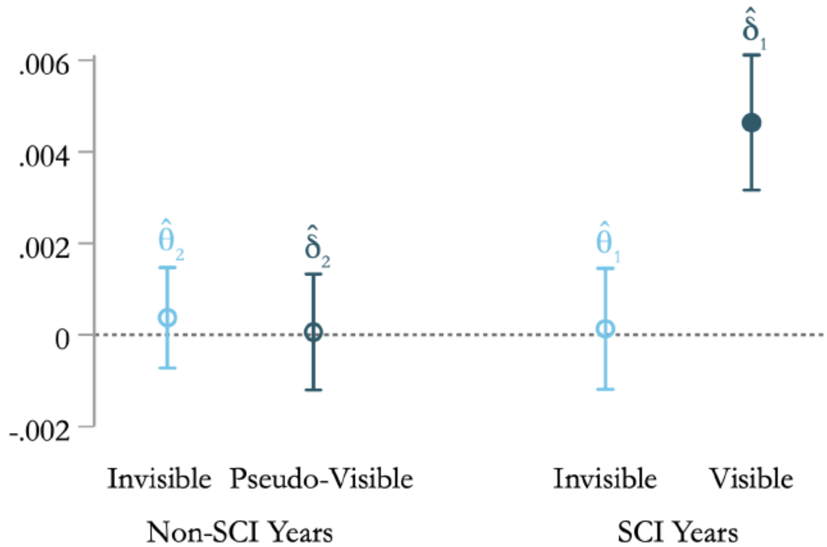
Notes: This table reports the estimates of Equation (7). This regression is based on the sample of all scientists who enter the World of Academia Database in the 1956 cross-section and are not full professors in 1956 and are observed in 1969. The dependent variable is an indicator equal to 1 if scientist i is a full professor in 1969, i.e., if i has been promoted to full professor. The first explanatory variable measures scientist i's individual rank in the distribution of visible citations (i.e., all citations that were visible in the SCI; see Section 3.1 for details). The second explanatory variable measures scientist i's individual rank in the distribution of *in*visible citations (i.e., all citations that were not visible in the SCI). Publications by Year separately measure the number of scientist i's publications in each year between 1956 and 1969. Publications by Journal separately measure the number of scientist i's publications in each journal (e.g., *Nature* or *Science*). Standard errors are clustered at the 1969-department-level. Significance levels: $***$ p<0.01, $**$ p<0.05, and $*$ p<0.1.

visibility (Table E.1). We also report results from a regression in which we restrict the analysis to citations in years in which the SCI was published. Again, results do not change (Table E.2). These robustness checks indicate that differences in the quality of citing journals or the timing of citations do not drive our results.

We also repeat the placebo test for this alternative career outcome. We test how much citations from journals that were initially covered by the SCI, but in years in which the SCI was not published, affect scientists' careers. We find that these pseudo-visible citations have no effect on a scientist's probability of being promoted (Table E.3). Only the citations that were truly visible in the SCI had an impact on scientists' promotions (Figure 9).

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 but also the allocation of resources in the sciences.

Figure 9: Plot of Coefficients from Placebo Test



Notes: The figure plots regression coefficients and corresponding 95 percent confidence intervals from a variant of Equation (2), where the dependent variable is an indicator equal to 1 if scientist i is promoted to full professor between 1956 and 1969. See also column (3) in Table E.3.

6 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 like the Impact Factor or the h-index are not only used to evaluate 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 the allocation of talent and for individual scientific careers.

In this paper, we use the introduction of the *Science Citation Index* to study these questions. We collect new data and 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. Second, we show that the effect is particularly pronounced for scientists at the top end of the citation distribution, and especially for "hidden stars" – well-cited scientists in lower-ranked departments. Third, we find that scientists from minority groups did not disproportionately benefit from citation metrics. Finally, we show that measuring citations increased the reliance on citation metrics in promotion decisions. Overall, our results demonstrate how the availability of citation metrics shapes modern science.

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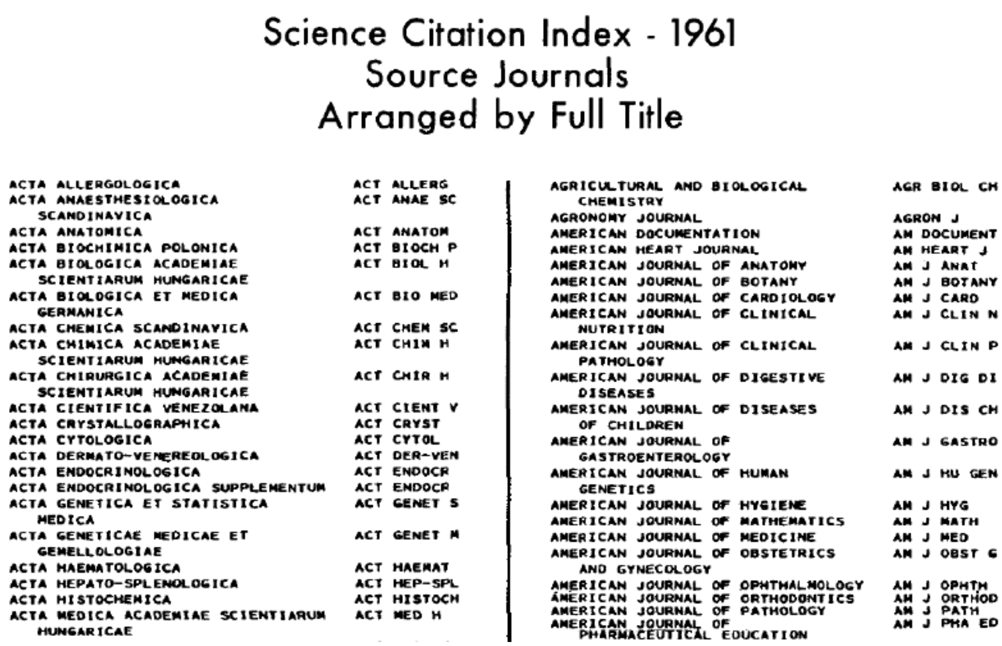
Appendix

The Appendix presents details on data collection and additional results:

- Appendix A provides further background on the SCI.
- Appendix B provides details on data collection.
- Appendix C reports additional robustness checks and findings on the analysis of assortative matching in Section 3.
- Appendix D reports additional findings on the heterogeneity analysis in Section 4.
- Appendix E reports additional findings on the promotion analysis in Section 5.

A Background on the SCI

Figure A.1: Example of Citing Journal List



Science Citation Index - 1961
Source Journals
Arranged by Full Title

ACTA ALLERGOLOGICA	ACT ALLERG
ACTA ANAESTHESIOLOGICA SCANDINAVICA	ACT ANAE SC
ACTA ANATOMICA	ACT ANATOM
ACTA BIOCHIMICA POLONICA	ACT BIOCH P
ACTA BIOLOGICA ACADEMIAE SCIENTIARUM HUNGARICAE	ACT BIOL H
ACTA BIOLOGICA ET MEDICA GERMANICA	ACT BIO MED
ACTA CHEMICA SCANDINAVICA	ACT CHEM SC
ACTA CHIMICA ACADEMIAE SCIENTIARUM HUNGARICAE	ACT CHIM H
ACTA CHIRURGICA ACADEMIAE SCIENTIARUM HUNGARICAE	ACT CHIR H
ACTA CIENTIFICA VENEZOLANA	ACT CIENT V
ACTA CRYSTALLOGRAPHICA	ACT CRYST
ACTA CYTOLOGICA	ACT CYTOL
ACTA DERMATO-VENEREOLOGICA	ACT DER-VEN
ACTA ENDOCRINOLOGICA	ACT ENDOCR
ACTA ENDOCRINOLOGICA SUPPLEMENTUM	ACT ENDOCR
ACTA GENETICA ET STATISTICA MEDICA	ACT GENET S
ACTA GENETICAE MEDICAE ET GEMELLOLOGIAE	ACT GENET M
ACTA HAEMATOLOGICA	ACT HAEMAT
ACTA HEPATO-SPLENOLOGICA	ACT HEP-SPL
ACTA HISTOCHEMICA	ACT HISTOCH
ACTA MEDICA ACADEMIAE SCIENTIARUM HUNGARICAE	ACT MED H
AGRICULTURAL AND BIOLOGICAL CHEMISTRY	AGR BIOL CH
AGRONOMY JOURNAL	AGRON J
AMERICAN DOCUMENTATION	AM DOCUMENT
AMERICAN HEART JOURNAL	AM HEART J
AMERICAN JOURNAL OF ANATOMY	AM J ANAT
AMERICAN JOURNAL OF BOTANY	AM J BOTANY
AMERICAN JOURNAL OF CARDIOLOGY	AM J CARD
AMERICAN JOURNAL OF CLINICAL NUTRITION	AM J CLIN N
AMERICAN JOURNAL OF CLINICAL PATHOLOGY	AM J CLIN P
AMERICAN JOURNAL OF DIGESTIVE DISEASES	AM J DIG DI
AMERICAN JOURNAL OF DISEASES OF CHILDREN	AM J DIS CH
AMERICAN JOURNAL OF GASTROENTEROLOGY	AM J GASTRO
AMERICAN JOURNAL OF HUMAN GENETICS	AM J HU GEN
AMERICAN JOURNAL OF HYGIENE	AM J HYG
AMERICAN JOURNAL OF MATHEMATICS	AM J MATH
AMERICAN JOURNAL OF MEDICINE	AM J MED
AMERICAN JOURNAL OF OBSTETRICS AND GYNECOLOGY	AM J OBST G
AMERICAN JOURNAL OF OPHTHALMOLOGY	AM J OPHTH
AMERICAN JOURNAL OF ORTHODONTICS	AM J ORTHOD
AMERICAN JOURNAL OF PATHOLOGY	AM J PATH
AMERICAN JOURNAL OF PHARMACEUTICAL EDUCATION	AM J PHA ED

Notes: This figure shows the first page of the "Source Journal List" of the 1961 SCI (Garfield, 1963b). This is a complete list of all 613 citing journals, from which citations were indexed for the 1961 SCI. We construct visible citations based on this list and the analogous lists from the 1964 to 1969 SCIs (see Section 2.2).

Figure A.2: Internal Correspondence at Ohio State University

THE OHIO STATE UNIVERSITY LIBRARIES
Chemistry Library
COLUMBUS 10, OHIO

LEWIS C. BRANSCOMB
Director of Libraries

September 21, 1965

Professor Hyman W. Kritzer
Assistant Director, Public Services
Main Library, 1858 Neil Avenue
Campus

Dear Professor Kritzer:

I would like to place a subscription for the Science Citation Index for Chemistry Library. In view of the scarcity of funds for periodical subscriptions, I am sending the order to you for your approval and assistance.

A poll of some of the faculty in the Chemistry Department revealed that, without exception, all the younger men would like to have SCI available for use in Chemistry Library. The senior faculty are not as emphatic but would like to have it available also.

Since SCI definitely complements the Chemical Abstracts approach to the literature and since placing it in Chemistry Library would mean fairly close access for other science departments in the area, I think special consideration should be given to our request for a subscription.

Sincerely,

Virginia E. Yagello
Virginia E. Yagello
Chemistry Librarian

VEY:kk

Enclosures: Correspondence to Chemistry faculty with comments attached.

Notes: In this letter, the chemistry librarian at Ohio State University requested a second copy of the SCI to be placed in the library of the chemistry department, in addition to the existing copy at the medical library. It shows that as early as 1965 there was large demand by chemists at Ohio State to use the SCI. We thank archivists at Ohio State library for sharing this document.

B Further Details on Data

B.1. Data on Scientists

In Section 4, we report results on the heterogeneous effect of citation metrics. In particular, in Section 4.3, we report differential results for women and for people with Asian, Hispanic, or Jewish names. We manually tag individual scientists as members of one of those groups. Gender coding is based on the gender coding in Iaria et al. (2022). We code Jewish names based on work from Benetti et al. (2023).

The coding of Hispanic and Asian names is based on data from the U.S. census. We draw a list of Hispanic names from Name Census (2023b). From this list, we select all surnames with a conditional probability of self-identifying as Hispanic of more than 25%. We then tag as Hispanic all academics in our dataset who have one of these names. Similarly, we draw a list of the most common Asian names from Name Census (2023a). From this list, we select all surnames with a conditional probability of self-identifying as Asian or Pacific Islander of more than 50%.[29] We then tag as Asian all academics in our dataset who have one of these names.

[29] The different cutoffs reflect different assimilation patterns of the various immigrant groups. Results are very similar if we impose the same cutoffs for both groups.

B.2. Department Rankings

The following six tables list the top 20 departments according to our self-constructed rankings (by average citations and by average publications in a department) and according to survey-based rankings from the 1960s and 1970s. Across different rankings for the same subject, it is often the same departments that are ranked highly.

Table B.1: Top 20 Departments: Biochemistry

Rank	Citations Ranking	Publications Ranking	Cartter Ranking	Roose-Andersen Ranking
1	Stanford	Washington	Harvard	Harvard
2	Rockefeller	Harvard	U.C. Berkeley	U.C. Berkeley
3	Johns Hopkins	Stanford	Stanford	Stanford
4	Washington	U.C. Berkeley	Rockefeller	Rockefeller
5	Harvard	Dartmouth	Wisconsin	Wisconsin
6	Kentucky	Wisconsin	M.I.T.	Cal. Tech.
7	U.C. Berkeley	Kentucky	Cal. Tech.	M.I.T.
8	Dartmouth	Johns Hopkins	Johns Hopkins	Brandeis
9	Wisconsin	Virginia Polytechnic Institute	Brandeis	Cornell
10	Case Western Reserve	U.C. Davis	Illinois	Johns Hopkins
11	Brandeis	Illinois	Columbia	U.C.L.A.
12	Duke	Kansas	Western Reserve	Duke
13	U.C. Davis	Saint Louis	N.Y.U.	U.C. San Diego
14	Utah	Duke	Washington	Washington
15	U.C.L.A.	Rockefeller	Duke	Yeshiva
16	Columbia	U.C.L.A.	Michigan	Chicago
17	Pennsylvania	Columbia	Pennsylvania	Illinois
18	Chicago	Case Western Reserve	Yeshiva	Princeton
19	Illinois	Rice	Chicago	Western Reserve
20	Saint Louis	Brandeis	U.C.L.A.	N.Y.U.

Notes: This table lists the top 20 biochemistry departments based on four different department rankings. The first column reports our self-constructed ranking based on the average number of citations (between 1956 and 1969, to publications between 1956 and 1969) of all scientists employed at the department in 1969. The second column reports our self-constructed ranking based on the average number of publications (between 1956 and 1969) of all scientists employed at the department in 1969. The third column reports the ranking from Cartter (1966). The fourth column reports the ranking from Roose and Andersen (1970). Where departments are ranked equally (in any of the four rankings), they are reported in alphabetical order in this table. In the regression analysis, they are given the same rank.

Table B.2: Top 20 Departments: Biology

Rank	Citations Ranking	Publications Ranking	Cartter Ranking	Roose-Andersen Ranking
1	Rockefeller	Albion College	U.C. Berkeley	Harvard
2	Albion College	Millikin	Harvard	U.C. Berkeley
3	Princeton	Texas	Cal. Tech.	M.I.T.
4	Harvard	Georgetown College	Johns Hopkins	Cal. Tech.
5	U.C. San Diego	U.C. San Diego	Rockefeller	Rockefeller
6	Stanford	Rockefeller	Wisconsin	Wisconsin
7	Cal. Tech.	U.C. Riverside	Illinois	Stanford
8	Texas	Wisconsin	Michigan	Washington
9	Syracuse	Princeton	Stanford	U.C. San Diego
10	U.C. Berkeley	U.C. Berkeley	Minnesota	Yale
11	Brandeis	U.C. Davis	Princeton	Chicago
12	Yale	Brandeis	Indiana	Illinois
13	Johns Hopkins	Stanford	Duke	Cornell
14	Notre Dame	Notre Dame	Cornell	Johns Hopkins
15	Winthrop College	Whitman College	Yale	U.C. Davis
16	Chicago	Mount Holyoke College	U.C.L.A.	Michigan
17	Georgetown	Alma College	Purdue	Duke
18	U.C. Davis	U.C. Santa Barbara	Western Reserve	U.C.L.A.
19	U.C. Santa Barbara	Illinois	Washington	Brandeis
20	Wisconsin	Central College, Pella	Chicago	Indiana

Notes: This table lists the top 20 biology departments based on four different department rankings. The first column reports our self-constructed ranking based on the average number of citations (between 1956 and 1969, to publications between 1956 and 1969) of all scientists employed at the department in 1969. The second column reports our self-constructed ranking based on the average number of publications (between 1956 and 1969) of all scientists employed at the department in 1969. The third column reports the ranking from Cartter (1966). While the Cartter ranking does not report rankings for biology overall, it does report rankings for five subfields of biology (Bacteriology/Microbiology, Botany, Entomology, Physiology, and Zoology). Based on these rankings, we construct an overall score for biology by taking the average rank of a department in the five reported subfields of biology. The fourth column reports the ranking from Roose and Andersen (1970). While the Roose-Andersen ranking does not report results for biology overall, it does report rankings for eight subfields of biology (Botany, Developmental Biology, Entomology, Microbiology, Molecular Biology, Physiology, Population Biology, and Zoology). Based on these rankings, we construct an overall score for biology by taking the average rank of a department in the eight reported subfields of biology. Where departments are ranked equally (in any of the four rankings), they are reported in alphabetical order in this table. In the regression analysis, they are given the same rank.

Table B.3: Top 20 Departments: Chemistry

Rank	Citations Ranking	Publications Ranking	Cartter Ranking	Roose-Andersen Ranking
1	U.C. Irvine	U.C. Santa Barbara	Harvard	Harvard
2	Stanford	Thiel College	Cal. Tech.	Cal. Tech.
3	U.C. Santa Barbara	Stanford	U.C. Berkeley	U.C. Berkeley
4	Harvard	U.C. Riverside	M.I.T.	Stanford
5	U.C.L.A.	U.C. Irvine	Stanford	M.I.T.
6	U.C. Riverside	Southern California	Illinois	Illinois
7	Illinois	College of Forestry at Syracuse	Columbia	U.C.L.A.
8	College of Forestry at Syracuse	Illinois	Wisconsin	Chicago
9	Cal. Tech.	Iowa State	U.C.L.A.	Columbia
10	Northwestern	Univeristy of Utah	Chicago	Cornell
11	Thiel College	Northwestern	Cornell	Wisconsin
12	Southern California	California	Yale	Yale
13	Iowa State	Texas	Princeton	Princeton
14	Univeristy of Utah	Case Western Reserve	Northwestern	Northwestern
15	U.C. Berkeley	Pennsylvania	Minnesota	Iowa State
16	Columbia	Johns Hopkins	Iowa State	Purdue
17	Notre Dame	U.C. Davis	Ohio State	U.C. San Diego
18	Texas	Duke	Purdue	Ohio State
19	California	Iowa State	Michigan	Texas
20	Johns Hopkins	Harvard	Indiana	Indiana

Notes: This table lists the top 20 chemistry departments based on four different department rankings. The first column reports our self-constructed ranking based on the average number of citations (between 1956 and 1969, to publications between 1956 and 1969) of all scientists employed at the department in 1969. The second column reports our self-constructed ranking based on the average number of publications (between 1956 and 1969) of all scientists employed at the department in 1969. The third column reports the ranking from Cartter (1966). The fourth column reports the ranking from Roose and Andersen (1970). Where departments are ranked equally (in any of the four rankings), they are reported in alphabetical order in this table. In the regression analysis, they are given the same rank.

Table B.4: Top 20 Departments: Mathematics

Rank	Citations Ranking	Publications Ranking	Cartter Ranking	Roose-Andersen Ranking
1	Princeton	U.C. Santa Barbara	Harvard	U.C. Berkeley
2	Virginia Polytechnic Institute	U.C. Riverside	U.C. Berkeley	Harvard
3	Stanford	Harvard	Princeton	Princeton
4	Chicago	Princeton	Chicago	Chicago
5	Institute for Advanced Study, Princeton	Carnegie-Mellon	M.I.T.	M.I.T.
6	Johns Hopkins	Washington	Stanford	Stanford
7	Harvard	Johns Hopkins	Yale	Yale
8	Columbia	Chicago	N.Y.U.	N.Y.U.
9	Brandeis	Rockefeller	Columbia	Wisconsin
10	U.C. Berkeley	Stanford	Wisconsin	Columbia
11	Carnegie-Mellon	Washington	Michigan	Michigan
12	Wisconsin	Columbia	Illinois	Cornell
13	Washington	Virginia	Cornell	Illinois
14	California	U.C. San Diego	Cal. Tech.	U.C.L.A.
15	Rockefeller	Wisconsin	Minnesota	Brandeis
16	Case Institute of Technology	Brandeis	U.C.L.A.	Brown
17	Brown	Yale	Washington	Cal. Tech.
18	Yale	Institute for Advanced Study, Princeton	Brown	Minnesota
19	Washington	Minnesota	Brandeis	Pennsylvania
20	Cornell	Oakland	John Hopkins	Washington

Notes: This table lists the top 20 mathematics departments based on four different department rankings. The first column reports our self-constructed ranking based on the average number of citations (between 1956 and 1969, to publications between 1956 and 1969) of all scientists employed at the department in 1969. The second column reports our self-constructed ranking based on the average number of publications (between 1956 and 1969) of all scientists employed at the department in 1969. The third column reports the ranking from Cartter (1966). The fourth column reports the ranking from Roose and Andersen (1970). Where departments are ranked equally (in any of the four rankings), they are reported in alphabetical order in this table. In the regression analysis, they are given the same rank.

Table B.5: Top 20 Departments: Medicine

Rank	**Citations Ranking**	**Publications Ranking**	**Cole-Lipton Ranking**
1	Rockefeller	New Mexico	Harvard
2	Harvard	Minnesota, Rochester	Johns Hopkins
3	Univeristy of Utah	Rutgers	Stanford
4	U.C. San Diego	U.C. San Diego	U.C. San Francisco
5	Minnesota, Rochester	Harvard	Yale
6	Texas	Amherst College	Columbia
7	Rutgers	Loretto Heights College	Duke
8	M.I.T.	Medical College of Virginia	Michigan
9	Washington	M.I.T.	Cornell
10	U.C. San Francisco	Washington	Washington, U.C.
11	Minnesota	Univeristy of Utah	Pennsylvania
12	Johns Hopkins	U.C.L.A.	Minnesota
13	U.C.L.A.	Johns Hopkins	U.C.L.A.
14	Kansas	Minnesota	Albert Einstein College of Medicine
15	Florida	Rockefeller	Chicago, Pritzker
16	Medical College of Virginia	Florida	Washington
17	New Mexico	U.C. San Francisco	Case Western Reserve
18	Washington	Southern California	Rochester
19	Stanford	Wagner College	Colorado
20	Case Western Reserve	Mississippi	U.C. San Diego

Notes: This table lists the top 20 biochemistry departments based on four different department rankings. The first column reports our self-constructed ranking based on the average number of citations (between 1956 and 1969, to publications between 1956 and 1969) of all scientists employed at the department in 1969. The second column reports our self-constructed ranking based on the average number of publications (between 1956 and 1969) of all scientists employed at the department in 1969. The third column reports the ranking from Cole and Lipton (1977). Since Cartter (1966) and Roose and Andersen (1970) do not report rankings for medical schools, we use the ranking by Cole and Lipton (1977) for medicine. Where departments are ranked equally (in any of the three rankings), they are reported in alphabetical order in this table. In the regression analysis, they are given the same rank.

Table B.6: Top 20 Departments: Physics

Rank	Citations Ranking	Publications Ranking	Cartter Ranking	Roose-Andersen Ranking
1	U.C. Berkeley	U.C. Riverside	U.C. Berkeley	U.C. Berkeley
2	U.C. Riverside	U.C. San Diego	Cal. Tech.	Cal. Tech.
3	U.C. San Diego	Lycoming College	Harvard	Harvard
4	Rockefeller	U.C. Santa Barbara	Princeton	Princeton
5	U.C. Santa Barbara	Kentucky Wesleyan College	Stanford	M.I.T.
6	Stanford	California	M.I.T.	Stanford
7	Chicago	Goshen College	Columbia	Columbia
8	Princeton	Harvard	Illinois	Illinois
9	Columbia	Chicago	Cornell	Chicago
10	U.C. Irvine	Rockefeller	Chicago	Cornell
11	Pennsylvania	Columbia	Yale	U.C. San Diego
12	Harvard	Princeton	Wisconsin	Yale
13	Pittsburgh	Pennsylvania	Michigan	Wisconsin
14	Yale	Stanford	Rochester	Michigan
15	Cal. Tech.	U.C. Berkeley	Pennsylvania	Pennsylvania
16	Brown	Pittsburgh	Maryland	Maryland
17	State University of New York	Brown	Minnesota	Rockefeller
18	Notre Dame	Iowa State	Washington	Rochester
19	Washington	Notre Dame	Johns Hopkins	U.C.L.A.
20	Illinois	Washington	U.C.L.A.	Minnesota

Notes: This table lists the top 20 physics departments based on four different department rankings. The first column reports our self-constructed ranking based on the average number of citations (between 1956 and 1969, to publications between 1956 and 1969) of all scientists employed at the department in 1969. The second column reports our self-constructed ranking based on the average number of publications (between 1956 and 1969) of all scientists employed at the department in 1969. The third column reports the ranking from Cartter (1966). The fourth column reports the ranking from Roose and Andersen (1970). Where departments are ranked equally (in any of the four rankings), they are reported in alphabetical order in this table. In the regression analysis, they are given the same rank.

C Additional Findings: Assortative Matching

C.1. Additional Robustness Checks

Table C.1: Robustness Check: Alternative Measures of Department Quality

	Dependent variable: Department rank				*Indicator*
	(1)	(2)	(3)	(4)	(5)
Department ranking based on:	Leave-out mean of citations	Mean of citations	Leave-out mean of publications	Mean of publications	Top 5 department
Panel A: Department rankings from 1969					
Rank Visible Citations	0.262***	0.304***	0.272***	0.303***	0.00026**
	(0.034)	(0.029)	(0.033)	(0.028)	(0.00011)
Rank Invisible Citations	0.067***	0.083***	0.054***	0.060***	-0.00001
	(0.021)	(0.020)	(0.020)	(0.019)	(0.00009)
P-value (Rank Visible = Rank Invisible)	< 0.001	< 0.001	< 0.001	< 0.001	0.094
Observations	26,404	26,404	26,404	26,404	26,404
R^2	0.147	0.203	0.148	0.207	0.069
Panel B: Department rankings from 1956					
Rank Visible Citations	0.155***	0.167***	0.144***	0.162***	0.00067**
	(0.039)	(0.040)	(0.038)	(0.041)	(0.00034)
Rank Invisible Citations	0.027	0.022	0.005	0.006	-0.00025
	(0.027)	(0.027)	(0.026)	(0.027)	(0.00020)
P-value (Rank Visible = Rank Invisible)	0.002	< 0.001	< 0.001	< 0.001	0.073
Observations	19,650	19,650	19,650	19,650	19,650
R^2	0.061	0.060	0.058	0.058	0.031
Subject Fixed Effects	Yes	Yes	Yes	Yes	Yes
Publications by Year × Subject	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the estimates of Equation (1) for alternative dependent variables. In Panel A, we report department rankings based on all scientists affiliated with a certain department in 1969. In Panel B, we report department rankings based on all scientists affiliated with a certain department in 1956. For scientists who in 1969 are affiliated with departments that did not exist in 1956, the ranking is not available. This results in a smaller sample size in Panel B. In column (1), we measure the department rank as the leave-out mean percentile of the citation distribution. In column (2), we measure the department rank as the percentile in the citation distribution. In column (3), we measure the department rank as the leave-out mean percentile of the publication distribution. In column (4), we measure the department rank as the percentile of the publication distribution. In column (5), the dependent variable is an indicator of being affiliated with a top-five department, as measured by average citations. The first explanatory variable measures scientist i's individual rank in the distribution of visible citations (i.e., all citations that were visible in the SCI; see Section 3.1 for details). The second explanatory variable measures scientist i's individual rank in the distribution of *in*visible citations (i.e., all citations that were not visible in the SCI). Control variables are measured as in Table 3. Standard errors are clustered at the department level. Significance levels: $***$ p<0.01, $**$ p<0.05, and $*$ p<0.1.

Figure C.1: Illustration of Variation Used in Additional Tests

(a) Main Analysis

	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

(b) Robustness: Consistent Journal Set

	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

(c) Robustness: Only SCI years

	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

(d) Placebo Test

	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: The four panels illustrate the sets of citations used for the robustness checks in Section 3.3 and the placebo test in Section 3.4. As in Table 2, these tables illustrate citations for a hypothetical scientist. Panel (a) illustrates the variation used in the main analysis (see Table 3). Numbers in dark blue cells indicate citations that were visible in the SCI because the citation occurred in a journal and year (1961, or 1964-69) that was covered by the SCI. Numbers in light blue cells indicate citations that were invisible, but are observable today. Panel (b) illustrates the variation used in the robustness check that restricts citations to a consistent set of journals (see Table 4). We disregard citations in journals that were not covered by the first SCI in 1961 (here: journals B and C), and focus only on citations in journals that were covered by the 1961 SCI (here: journal A). Numbers in dark blue cells indicate citations that were visible in the SCI, i.e., citations from 1961, or 1964-69. Numbers in light blue cells indicate citations that were invisible because they came from years not covered by the SCI. Panel (c) illustrates the variation used in the robustness check that restricts citations to years for which the SCI was published (see Table 5). We disregard citations from years in which the SCI was not published, and focus only on citations in years that were covered by the SCI, i.e., citations from 1961, or 1964-69. Numbers in dark blue cells indicate citations that were visible in the SCI, because they came from journals indexed by the SCI. Numbers in light blue cells indicate citations that were invisible because they came from journals not covered by the SCI. Panel (d) illustrates the variation used in the placebo test (see Table 6). As in panel (c) we partition citations by whether they appeared in years covered by the SCI (blue) or not (green). Numbers in dark green cells indicate pseudo-visible citations, i.e., citations that were in fact invisible (because they came from years not covered by the SCI) but would have been visible had the SCI been published for those years. Numbers in light green cells indicate invisible citations for years in which the SCI was not published.

Table C.2: Robustness Check: External Department Rankings

	Dependent variable: Department rank				
	(1)	(2)	(3)	(4)	(5)
Panel A: Cartter Ranking					
Rank Visible Citations	0.237***	0.245***	0.218***	0.192***	0.188***
	(0.030)	(0.029)	(0.031)	(0.029)	(0.029)
Rank Invisible Citations	0.054**	0.058**	0.041*	0.041*	0.036
	(0.027)	(0.023)	(0.022)	(0.022)	(0.023)
P-value (Rank Visible = Rank Invisible)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Observations	26,404	26,404	26,404	26,404	26,404
R^2	0.085	0.085	0.101	0.202	0.231
Panel B: Roose-Andersen Ranking					
Rank Visible Citations	0.262***	0.275***	0.242***	0.217***	0.214***
	(0.031)	(0.029)	(0.032)	(0.030)	(0.030)
Rank Invisible Citations	0.045*	0.052**	0.033	0.033	0.029
	(0.026)	(0.022)	(0.022)	(0.022)	(0.022)
P-value (Rank Visible = Rank Invisible)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Observations	26,404	26,404	26,404	26,404	26,404
R^2	0.092	0.093	0.110	0.207	0.236
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

Notes: The table reports the estimates of Equation (1) where the dependent variable is based on reputational department rankings from Cartter (1966) in Panel A and from Roose and Andersen (1970) in Panel B. In both panels, we use the first comprehensive ranking of medical schools by Cole and Lipton (1977) for the department rankings of scientists in medicine. Using these field-specific rankings, we assign each department its percentile rank. To avoid unnecessary sample selection for this robustness check, we assign unranked universities to the average rank between 1 and the lowest-ranked university in those rankings. The first explanatory variable measures scientist i's individual rank in the distribution of visible citations (i.e., all citations that were visible in the SCI; see Section 3.1 for details). The second explanatory variable measures scientist i's individual rank in the distribution of *in*visible citations (i.e., all citations that were not visible in the SCI). Publications by Year separately measure the number of scientist i's publications in each year between 1956 and 1969. Publications by Journal separately measure the number of scientist i's publications in each journal (e.g., *Nature* or *Science*). Standard errors are clustered at the department level. Significance levels: $***$ p<0.01, $**$ p<0.05, and $*$ p<0.1.

Table C.3: Robustness Check: Alternative Transformations of Citation Counts

	Dependent variable: Department rank				
	(1)	(2)	(3)	(4)	(5)
Citations variable transformation:	Main specification	Standard-ized	Winsorized & std.	Asinh	Only 1956-65 citations
Visible Citations	0.262***	2.762***	4.753***	2.550***	0.203***
	(0.034)	(0.666)	(0.542)	(0.457)	(0.027)
Invisible Citations	0.067***	-0.444	0.702	1.032***	0.120***
	(0.021)	(0.607)	(0.457)	(0.253)	(0.025)
Subject Fixed Effects	Yes	Yes	Yes	Yes	Yes
Publications by Year × Subject	Yes	Yes	Yes	Yes	Yes
P-value (Visible = Invisible)	< 0.001	0.006	< 0.001	0.004	0.015
Observations	26,404	26,404	26,404	26,404	26,404
R^2	0.147	0.102	0.111	0.141	0.135

Notes: The table reports the estimates of Equation (1) for alternative dependent variables. In column (1), we measure the department rank as the leave-out mean percentile of the citation distribution. (Departments and individuals without citations are assigned a percentile according to the midpoint between 0 and the lowest percentile with positive citations.) In column (2), the dependent variable is equal to the leave-out mean of standardized citations of scientists affiliated with a department. We standardize citations by subject. In column (3), the dependent variable is defined as in column (2), but to reduce the weight of outliers, we winsorize citation counts at the 99th percentile and then standardize them. In column (4), the dependent variable is equal to the leave-out mean of citations which we transform with the invisible hyperbolic sine transformation. In column (5), we measure the department rank as the leave-out mean percentile of the distribution of citations between 1956 and 1965 (instead of 1956-1969). (Summary statistics for the citation variables when restricting to citation in 1956-1965: Mean visible citations is 32.4, standard deviation of visible citations is 97.0, mean invisible citations is 43.5, standard deviation of visible citations is 133.3.) The first explanatory variable measures scientist i's individual rank in the distribution of visible citations (i.e., all citations that were visible in the SCI; see Section 3.1 for details). The second explanatory variable measures scientist i's individual rank in the distribution of *in*visible citations (i.e., all citations that were not visible in the SCI). Control variables are measured as in Table 3. Standard errors are clustered at the department level. Significance levels: $***$ p<0.01, $**$ p<0.05, and $*$ p<0.1.

Table C.4: Robustness Check: Alternative Sample Restrictions

	Dependent variable: Department rank		
	(1)	(2)	(3)
Sample restriction:	Full sample	Num. of cit. > 0	Size of dept. > 10
Rank Visible Citations	0.262***	0.287***	0.201***
	(0.034)	(0.037)	(0.034)
Rank Invisible Citations	0.067***	0.088***	0.059***
	(0.021)	(0.020)	(0.021)
Subject Fixed Effects	Yes	Yes	Yes
Publications by Year × Subject	Yes	Yes	Yes
P-value (Rank Visible = Rank Invisible)	< 0.001	< 0.001	< 0.001
Observations	26,404	16,520	21,869
R^2	0.147	0.130	0.132

Notes: The table reports the estimates of Equation (1) for alternative subsamples. In column (1), we use the full sample, i.e., it is equivalent to column (3) in Table 3. Column (2) reports results from the same regression for the subsample of scientists who have more than zero citations. Column (3) reports results for the subsample of scientists who are employed at departments with at least 10 scientists. The dependent variable is the department rank of scientist i in 1969 measured in percentiles. To construct the department rank, we calculate the leave-out mean of citations of all scientists in the department of scientist i. We then assign the rank based on the percentile in the distribution of leave-out mean citations. The first explanatory variable measures scientist i's individual rank in the distribution of visible citations (i.e., all citations that were visible in the SCI; see Section 3.1 for details). The second explanatory variable measures scientist i's individual rank in the distribution of *in*visible citations (i.e., all citations that were not visible in the SCI). Control variables are measured as in Table 3. Standard errors are clustered at the department level. Significance levels: $***$ p<0.01, $**$ p<0.05, and $*$ p<0.1.

C.2. Additional Findings

Table C.5: Heterogeneous Effect for Leaving Academia

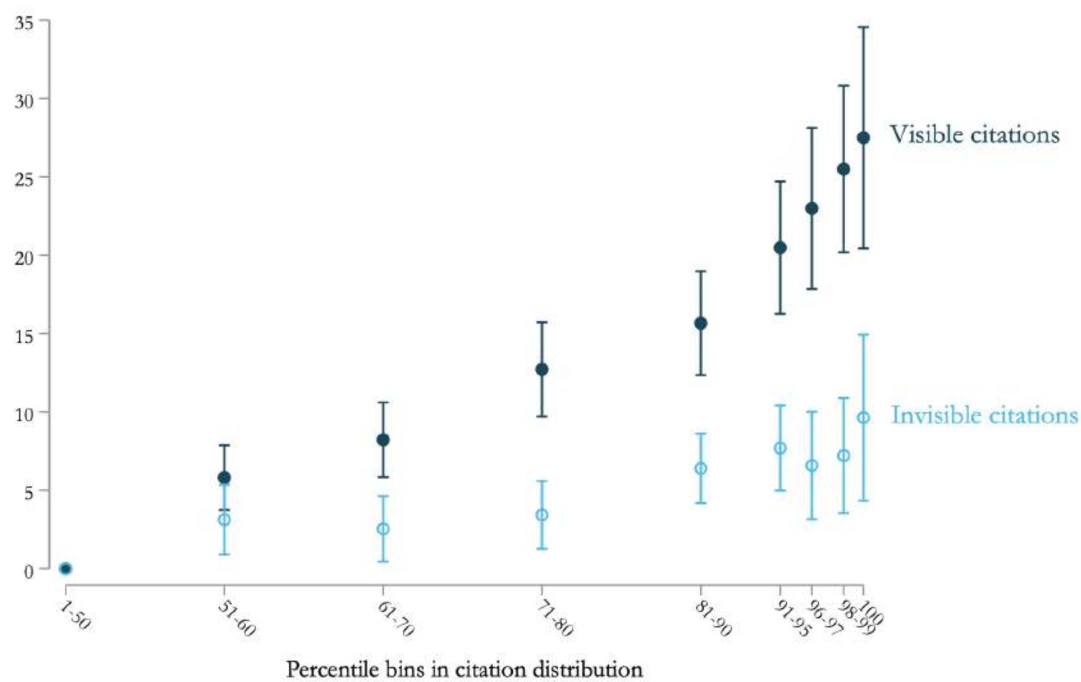
	Dependent variable: Left academia between 1956 and 1969				
	(1)	(2)	(3)	(4)	(5)
Sample restriction:	Full sample	Dept. below 75th pct.	Dept. above 75th pct.	Dept. below 90th pct.	Dept. above 90th pct.
Rank Citations Visible	-0.0029***	-0.0026***	-0.0031***	-0.0029***	-0.0034***
	(0.0005)	(0.0007)	(0.0006)	(0.0005)	(0.0011)
Rank Citations Invisible	0.0001	0.0006	-0.0003	0.0006	-0.0005
	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0013)
Subject Fixed Effects	Yes	Yes	Yes	Yes	Yes
Publications by Year × Subject	Yes	Yes	Yes	Yes	Yes
P-value (Rank Visible = Rank Invisible)	0.002	0.023	0.014	0.001	0.199
Observations	11,625	5,618	6,007	9,490	2,135
R^2	0.104	0.053	0.195	0.078	0.251

Notes: This table reports estimates of Equation (3) for subsamples of scientists at high-ranked or low-ranked departments. The dependent variable is an indicator taking value 1 if scientist i was observed in the 1956 cross-section, but not in the 1969 cross-section, i.e., if i left academia. This regression is based on the 1956 cross-section of scientists who were not full professors in 1956. Column (1) reports the main specification for reference (see also column (3) in Panel A of Table 7). Columns (2) and (3) report regression results based on sample splits at the 75th percentile in the department-ranking distribution. Columns (4) and (5) report regression results based on sample splits at the 90th percentile in the department-ranking distribution. The first explanatory variable measures scientist i's rank in the distribution of visible citations (i.e., all citations that were visible in the SCI; see Section 3.1 for details). The second explanatory variable measures scientist i's rank in the distribution of *in*visible citations (i.e., all citations that were not visible in the SCI). Publications by Year separately measure the number of scientist i's publications in each year between 1942 and 1969. Standard errors are clustered at the 1956-department-level. Significance levels: $***$ p<0.01, $**$ p<0.05, and $*$ p<0.1.

D Additional Findings: Heterogeneity Analysis

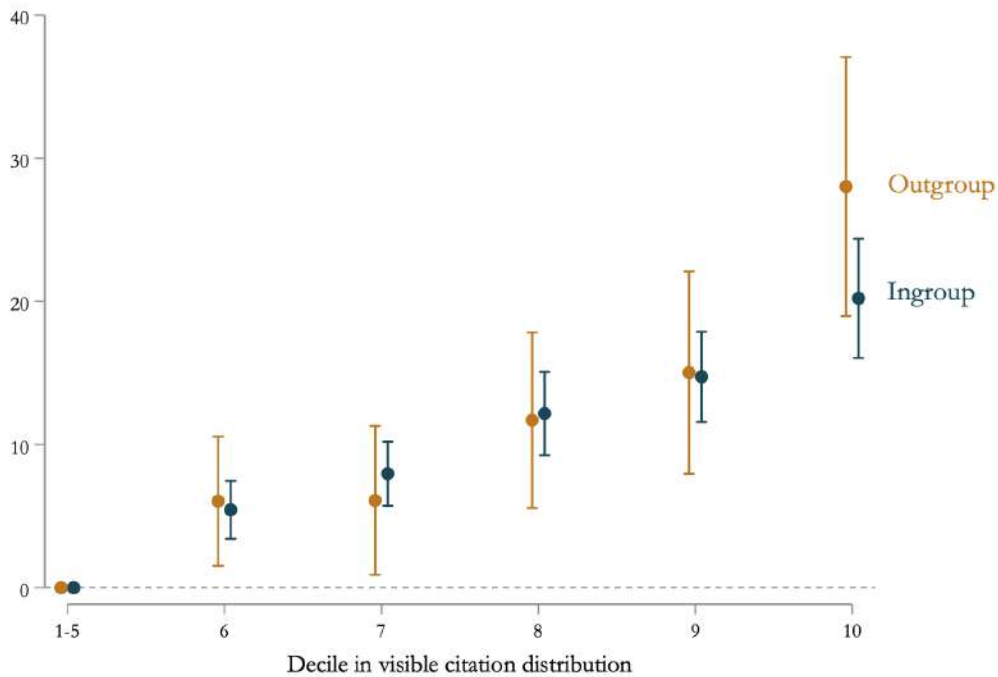
D.1. Heterogeneous Effect in Non-Parametric Analysis

Figure D.1: Heterogenous Effects by Percentile Rank



Notes: The figure plots regression coefficients δ_q (visible citations, dark blue) and θ_q (invisible citations, light blue) and corresponding 95 percent confidence intervals from a variant of equation 4. It differs from Figure 6 in that it splits up the 10th decile into smaller percentile bins.

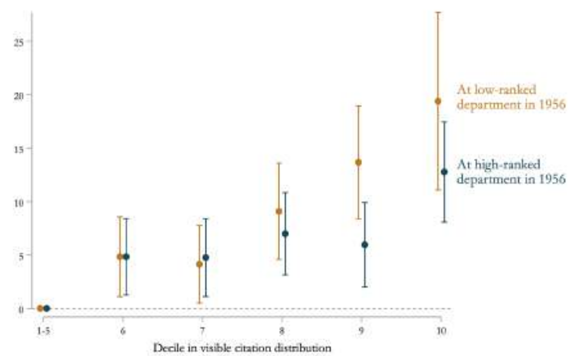
Figure D.2: Heterogenous Effects for Outgroup and Ingroup



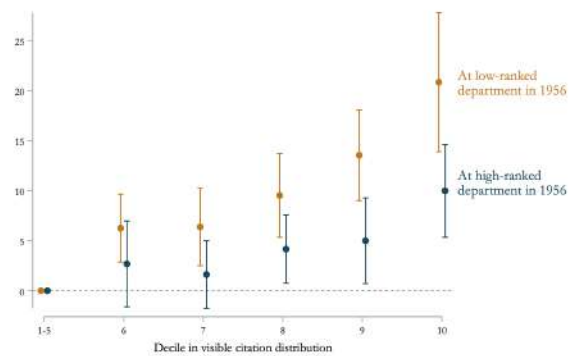
Notes: This figure plots regression coefficients analogous to δ_q^M (blue) and δ_q^m (brown), and corresponding 95 percent confidence intervals from Equation (6), i.e., it reports separate sets of coefficients for members of any outgroup (brown) and for scientists who are not part of some outgroup (blue). Being a member of any outgroup is defined as taking value 1 if a scientist is either female, or has an Asian, Hispanic, or Jewish name.

Figure D.3: Heterogeneous Effects for Peripheral Scientists

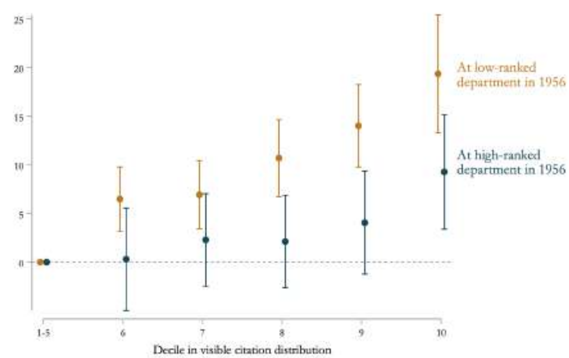
(a) Cutoff: 60th percentile



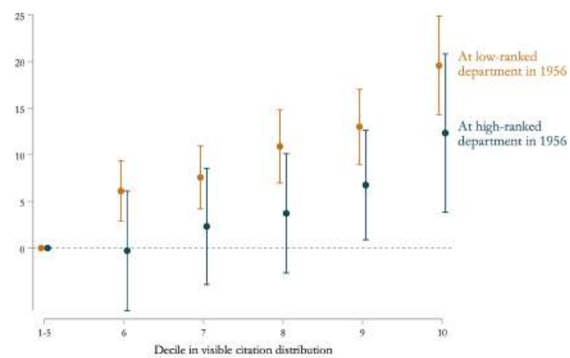
(b) Cutoff: 70th percentile



(c) Cutoff: 80th percentile



(d) Cutoff: 90th percentile



Notes: The four panels plot estimated regression coefficients δ_q^H (blue) and δ_q^L (brown), and corresponding 95 percent confidence intervals from Equation (5) for various cutoffs of high and low-ranked departments. In panel (a) we define low-ranked departments as those below the 60th percentile of the department ranking in 1956. In panel (b) we define low-ranked departments as those below the 70th percentile of the department ranking in 1956. In panel (c) we define low-ranked departments as those below the 80th percentile of the department ranking in 1956. In panel (d) we define low-ranked departments as those below the 90th percentile of the department ranking in 1956

D.2. Heterogeneous Effect on Assortative Matching in Main Analysis

In Sections 4.2 and 4.3, we perform heterogeneity analyses for scientists at low-ranked departments and for minority scientists, respectively. These are based on a non-parametric regression as outlined in Equations (5) and (6). Additionally, we report results regarding the heterogeneous effect of citation metrics on assortative matching based on a variant of the main specification in Equation (1):

$$\begin{aligned} Dep.\ Rank_i = {} & \delta \cdot Visible\,Citations_i + \delta^I \cdot Visible\,Citations_i \times Indicator_i \\ & + \theta \cdot Invisible\,Citations_i + \theta^I \cdot Invisible\,Citations_i \times Indicator_i \\ & + \omega \cdot Indicator_i + \pi \cdot Publications_i + Subject\,FE + \epsilon_i \end{aligned} \tag{D.1}$$

$Indicator_i$ takes value 1 if scientist i is member of a specific subgroup of scientists. In Table D.1, we report results for peripheral scientists, i.e., where the indicator captures whether a scientist was working at a low-ranked department in 1956. In Table D.2, we report results for minority scientists, i.e., where the indicator captures whether the scientist was part of a minority group.

Table D.1: Heterogeneous Effect on Assortative Matching for Peripheral Scientists

	Dependent variable: Department rank				
	(1)	(2)	(3)	(4)	(5)
Indicator:	Below 60	Below 70	Below 75	Below 80	Below 90
Rank Visible Citations	0.123***	0.092**	0.083**	0.084	0.185***
	(0.036)	(0.038)	(0.042)	(0.051)	(0.067)
Rank Invisible Citations	0.050	0.035	0.051	0.046	-0.061
	(0.038)	(0.043)	(0.048)	(0.058)	(0.052)
Rank Visible Citations × Indicator	0.096*	0.133**	0.144***	0.151**	0.052
	(0.056)	(0.053)	(0.055)	(0.062)	(0.076)
Rank Invisible Citations × Indicator	0.039	0.070	0.063	0.077	0.208***
	(0.057)	(0.058)	(0.061)	(0.067)	(0.061)
Indicator	-35.341***	-38.060***	-37.545***	-38.265***	-37.965***
	(3.695)	(3.824)	(4.242)	(4.805)	(6.024)
Subject Fixed Effects	Yes	Yes	Yes	Yes	Yes
Publications by Year × Subject	Yes	Yes	Yes	Yes	Yes
Observations	6,053	6,053	6,053	6,053	6,053
R^2	0.378	0.338	0.315	0.288	0.230

Notes: The table reports the estimates of Equation (D.1) for different subgroups in the data. The dependent variable is the department rank of scientist i in 1969 measured in percentiles. To construct the department rank, we calculate the leave-out mean of citations of all scientists in the department of scientist i. We then assign the rank based on the percentile in the distribution of leave-out mean citations. The first explanatory variable measures scientist i's individual rank in the distribution of visible citations (i.e., all citations that were visible in the SCI; see Section 3.1 for details). The second explanatory variable measures scientist i's individual rank in the distribution of *in*visible citations (i.e., all citations that were not visible in the SCI). The third and fourth explanatory variables are the interactions between these citation variables and an indicator taking value 1 if scientist i was based in a low-ranked department in 1956. These estimates capture the additional return on citations for these peripheral scientists. The fifth explanatory variable is the low-ranked department indicator itself. Since we require information on where a scientist was based in 1956, the sample of scientists used in this analysis is all scientists who appear in our data in both 1956 and 1969. We define low-ranked departments as those below a specific percentile in the 1956 department ranking. The different columns report results from regressions using different definitions of this variable: 60th percentile in column (1), 70th percentile in (2), 75th percentile in column (3), 80th percentile in column (4), and 90th percentile in column (5). Publications by Year separately measure the number of scientist i's publications in each year between 1956 and 1969. Standard errors are clustered at the department level. Significance levels: $***$ p<0.01, $**$ p<0.05, and $*$ p<0.1.

Table D.2: Heterogeneous Effect on Assortative Matching for Minority Scientists

	Dependent variable: Department rank					
	(1)	(2)	(3)	(4)	(5)	(6)
Indicator:	Main	Female	Asian	Hispanic	Jewish	Outgroup
Rank Visible Citations	0.262***	0.268***	0.262***	0.262***	0.262***	0.255***
	(0.034)	(0.038)	(0.034)	(0.034)	(0.034)	(0.032)
Rank Invisible Citations	0.067***	0.050**	0.068***	0.066***	0.066***	0.065***
	(0.021)	(0.021)	(0.022)	(0.021)	(0.021)	(0.021)
Rank Visible Citations × Indicator		-0.075	-0.040	-0.072	0.020	-0.020
		(0.053)	(0.077)	(0.170)	(0.208)	(0.047)
Rank Invisible Citations × Indicator		-0.016	-0.070	0.139	0.106	-0.011
		(0.058)	(0.085)	(0.170)	(0.221)	(0.048)
Indicator		-3.222	4.147	-2.239	-0.080	-6.235**
		(2.581)	(3.349)	(4.815)	(6.390)	(2.780)
Subject Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Publications by Year × Subject	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,404	23,497	26,404	26,404	26,404	26,404
R^2	0.147	0.152	0.147	0.147	0.148	0.154

Notes: The table reports the estimates of Equation (D.1) for different subgroups in the data. The dependent variable is the department rank of scientist i in 1969 measured in percentiles. To construct the department rank, we calculate the leave-out mean of citations of all scientists in the department of scientist i. We then assign the rank based on the percentile in the distribution of leave-out mean citations. The first explanatory variable measures scientist i's individual rank in the distribution of visible citations (i.e., all citations that were visible in the SCI; see Section 3.1 for details). The second explanatory variable measures scientist i's individual rank in the distribution of *in*visible citations (i.e., all citations that were not visible in the SCI). The third and fourth explanatory variables are the interactions between these citation variables and an indicator taking value 1 if scientist i is a member of a specific subgroup. These estimates capture the additional return on citations for members of these subgroups. The fifth explanatory variable is the subgroup indicator itself. Column (1) reports the main specification for reference (see column (3) in Table 3). Columns (2)-(5) report the results from regressions where the subgroup indicator takes value 1 if scientist i is a member of a specific subgroup: female in column (2), Asian in column (3), Hispanic in column (4), and Jewish in column (5). Column (6) reports the results from a regression where the subgroup indicator is 1 if scientist i is member of any one of these outgroups. Publications by Year separately measure the number of scientist i's publications in each year between 1956 and 1969. Standard errors are clustered at the department level. Significance levels: $***$ p<0.01, $**$ p<0.05, and $*$ p<0.1.

E Additional Findings: Promotions

Table E.1: Robustness Check: Citations From a Consistent Set of Journals

	Dependent variable: Promoted to Full Professor				
	(1)	(2)	(3)	(4)	(5)
Rank Visible Citations	0.0043***	0.0045***	0.0045***	0.0040***	0.0039**
	(0.0008)	(0.0008)	(0.0008)	(0.0013)	(0.0017)
Rank Invisible Citations	0.0007	0.0001	0.0004	-0.0001	-0.0002
	(0.0006)	(0.0006)	(0.0006)	(0.0011)	(0.0014)
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
P-value (Rank Visible = Rank Invisible)	0.004	0.001	0.002	0.060	0.140
Observations	2,906	2,906	2,906	2,906	2,906
R^2	0.138	0.145	0.157	0.395	0.423

Notes: This table reports the estimates of Equation (7). To construct citation ranks, we only consider citations in journals that were covered by the 1961 edition of the SCI. This regression is based on the sample of all scientists who enter the data in the 1956 cross-section and are not full professors in 1956 and are observed in 1969. The dependent variable is an indicator equal to 1 if scientist i is a full professor in 1969, i.e., if i has been promoted to full professor. The first explanatory variable measures scientist i's individual rank in the distribution of visible citations (i.e., all citations that were visible in the SCI; see Section 3.1 for details). The second explanatory variable measures scientist i's individual rank in the distribution of *in*visible citations (i.e., all citations that were not visible in the SCI). Publications by Year separately measure the number of scientist i's publications in each year between 1956 and 1969. Publications by Journal separately measure the number of scientist i's publications in each journal (e.g., *Nature* or *Science*). Standard errors are clustered at the 1969-department-level. Significance levels: $***$ p<0.01, $**$ p<0.05, and $*$ p<0.1.

Table E.2: Robustness Check: Citations Only From Years With SCI

	Dependent variable: Promoted to Full Professor				
	(1)	(2)	(3)	(4)	(5)
Rank Visible Citations	0.0045***	0.0047***	0.0048***	0.0037***	0.0036***
	(0.0005)	(0.0006)	(0.0006)	(0.0011)	(0.0014)
Rank Invisible Citations	0.0005	0.0002	0.0003	-0.0000	-0.0002
	(0.0005)	(0.0006)	(0.0006)	(0.0009)	(0.0011)
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
P-value (Rank Visible = Rank Invisible)	< 0.001	< 0.001	< 0.001	0.023	0.071
Observations	2,906	2,906	2,906	2,906	2,906
R^2	0.141	0.149	0.159	0.394	0.422

Notes: This table reports the estimates of Equation (7). To construct citation ranks, we only consider citations in years when the SCI was available (i.e., 1961, and 1964-1969). This regression is based on the sample of all scientists who enter the data in the 1956 cross-section and are not full professors in 1956 and are observed in 1969. The dependent variable is an indicator equal to 1 if scientist i is a full professor in 1969, i.e., if i has been promoted to full professor. The first explanatory variable measures scientist i's individual rank in the distribution of visible citations (i.e., all citations that were visible in the SCI; see Section 3.1 for details). The second explanatory variable measures scientist i's individual rank in the distribution of *in*visible citations (i.e., all citations that were not visible in the SCI). Publications by Year separately measure the number of scientist i's publications in each year between 1956 and 1969. Publications by Journal separately measure the number of scientist i's publications in each journal (e.g., *Nature* or *Science*). Standard errors are clustered at the 1969-department-level. Significance levels: $***$ p<0.01, $**$ p<0.05, and $*$ p<0.1.

Table E.3: Placebo Test: Predictiveness of Citations Before the SCI

	Dependent variable: Promoted to Full Professor			
	Only SCI years		Incl. non-SCI years	
	(1)	(2)	(3)	(4)
Rank Visible Citations (SCI years)	0.0048***	0.0036***	0.0046***	0.0035**
	(0.0006)	(0.0014)	(0.0008)	(0.0016)
Rank Invisible Citations (SCI years)	0.0003	-0.0002	0.0001	-0.0001
	(0.0006)	(0.0011)	(0.0007)	(0.0013)
Rank Pseudo-Visible Citations (non-SCI years)			0.0001	0.0004
			(0.0006)	(0.0013)
Rank Invisible Citations (non-SCI years)			0.0004	-0.0005
			(0.0006)	(0.0012)
Publications by Year × Subject	Yes	Yes	Yes	Yes
Publications by Journal × Subject		Yes		Yes
P-value (Visible = Invisible (SCI years))	< 0.001	0.071	< 0.001	0.097
P-value (Visible = Pseudo-Visible)			< 0.001	0.224
P-value (Invisible (SCI) = Invisible (non-SCI))			0.810	0.845
P-value (Pseudo-Visible = Invisible (non-SCI))			0.734	0.630
Observations	2,906	2,906	2,906	2,906
R^2	0.159	0.422	0.159	0.422

Notes: This table reports the estimates of Equation (2). The dependent variable is an indicator equal to 1 if scientist i is a full professor in 1969, i.e., if i has been promoted to full professor. This regression is based on the sample of all scientists who enter the data in the 1956 cross-section and are not full professors in 1956 and are observed in 1969. The first explanatory variable measures scientist i's individual rank in the distribution of visible citations in SCI years (i.e., all citations that were visible in the SCI; see Section 3.1 for details). The second explanatory variable measures scientist i's individual rank in the distribution of *in*visible citations in SCI years (i.e., all citations that were not visible in the SCI in 1961 and 1964-1969). The third explanatory variable measures scientist i's individual rank in the distribution of pseudo-visible citations in non-SCI years (i.e., all citations in journals that were contained in the SCI in 1961 but for years that were not covered in the SCI, i.e., 1956-1960 and 1962-1963). The fourth explanatory variable measures scientist i's individual rank in the distribution of *in*visible citations in non-SCI years (i.e., all citations in journals that were not contained in the SCI in 1961 and in years that were not covered, i.e., 1956-1960 and 1962-1963). Publications by Year separately measure the number of scientist i's publications in each year between 1956 and 1969. Publications by Journal separately measure the number of scientist i's publications in each journal (e.g., *Nature* or *Science*). Standard errors are clustered at the 1969-department level. Significance levels: $***$ p<0.01, $**$ p<0.05, and $*$ p<0.1. P-value from test $\theta_1 = \theta_2 = \delta_2$: 0.937 in column (3), 0.890 in column (4).