Measuring Science: Performance Metrics and the Allocation of Talent*

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June 26, 2024

Abstract

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

*We are grateful to Stefano DellaVigna and John Friedman, three knowledgeable referees, Ran Abramitzky, Nano Barahona, David Card, 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, Bristol, CERGE-EI, Essex, HEC, LMU Munich, Stanford, Surrey, and the 2023 BITSS Annual Meeting for insightful comments and suggestions. We are grateful to Alessandro Iaria and Lena Greska, who have greatly contributed to the construction of the World of Academia Database, which we use in this paper. We also thank Dan Gross for generously sharing data on NSF grants. Matthias Bing, Julia Geltinger, Peter Heinrich, Paulina Maier, Felix Radde, Nils Süßenbach, and Luca Veh provided excellent research assistance. Support by Deutsche Forschungsgemeinschaft through CRC TRR 190 (nr. 280092119) is gratefully acknowledged.

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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; Hsieh et al., 2019). As talent is scarce, private sector firms and universities increasingly rely on performance metrics to identify talented individuals (e.g., Hoffman 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 that quantifies how performance metrics affect the organization of science.

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

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

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

Similarly, increases in team production (e.g., Wuchty et al., 2007; Jones, 2009) may have spurred collaborations within departments and, hence, made department quality more critical for citations of individual scientists.

We estimate the causal effect of citation metrics by exploiting that, for technical reasons, the SCI only covered citations in a subset of years and journals. Only these citations became *visible* to the scientific community. In contrast, other citations remained *invisible* to contemporaries, yet are observable in modern citation data. The variation in the visibility of citations stems from two sources: variation in the coverage of citations (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. 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. Crucially, in the early years, the selection of citing journals was somewhat arbitrary because the lack of citation data meant that journal rankings did not exist.[1]

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

For our analysis, we combine new data on historical faculty rosters of 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 relative importance of visible to invisible citations. We find that visible citations are four times as predictive of scientists' department rank than invisible

[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).

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

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

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

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

The quality of citing journals and the timing of citations could interact to make visible citations more predictive for assortative matching. To address this concern, we introduce an additional specification. For this test, we partition the citation space into four mutually exclusive sets depending on where and when a scientist was cited: (1) *visible citations*: citations from journals that were indexed in the SCI in years when the SCI was published; (2) *pseudo-visible citations*: citations from journals that were indexed in the SCI in 1961 but from years when the SCI was not published; (3) *invisible citations (SCI years)*: citations from journals that were not indexed in the SCI in years when the SCI was published; and (4) *invisible citations (non-SCI years)*: citations from journals that were not indexed in the SCI in 1961 and from years when the SCI was not published.

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

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

Citation metrics may matter more in situations where peers did not have good information on the quality of a potential hire. We, therefore, explore whether citation metrics reduced information frictions across geographic and intellectual distance. We find that citation metrics only impacted moves to higher-ranked departments that were geographically far but not to departments that were geographically close. Similarly, we find that citation metrics only impacted moves to higher-ranked departments where the moving scientist had not been cited before the move. These results suggest that citation metrics helped overcome information frictions. Reducing these frictions may have enabled departments to discover scientists in lower-ranked departments, even if they had not interacted before.

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

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

This paper contributes to three different strands of the literature. First, our paper contributes to the body of literature on the economics of science and the creation of knowledge. The existing literature has shown that scientists have to process increasing amounts of knowledge to advance the scientific frontier (Jones, 2009) and that access to the knowledge frontier is crucial for producing science (Iaria et al., 2018). Additional contributions have studied the importance of superstar scientists (Azoulay et al., 2010), peer-effects and scientific productivity (e.g., Waldinger, 2010, 2012; Borjas and Doran, 2012), and the role of editors (e.g., Card and DellaVigna, 2020). More recently, increased attention has been paid to inefficiencies in the scientific process such as the Matthew Effect (Azoulay 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 sociological debate on this fundamental aspect of modern science (e.g., Lotka, 1926; Merton, 1968; Zuckerman and Merton, 1971; Wouters, 1999a, 2014; Muller and Peres, 2019; Biagioli and Lippman, 2020; Pardo-Guerra, 2022), there is no causal evidence on how performance metrics affect scientific careers.[2] Our paper is the first to provide causal evidence that citation metrics fundamentally impact the organization of science.

Second, our findings contribute to the literature on performance metrics in the labor market. As highlighted by the theoretical models of Holmstrom and Milgrom (1991) and Feltham and Xie (1994), the use of performance metrics shapes incentives of agents in the labor market. The key empirical challenge to estimating the impact of performance metrics is that, in most cases, it is impossible to measure performance before the introduction of a specific performance metric. As a result, researchers often lack a valid counterfactual. This makes empirical evidence on how performance metrics affect the allocation of talent

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

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 at the time and, importantly, what was not part of that information set.[3]

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

I The Science Citation Index: Background and Data

I.A The Creation of the Science Citation Index

The SCI was the first systematic international and interdisciplinary citation index. During the 1950s, Eugene Garfield and his newly founded *Institute for Scientific Information* (ISI) developed the technology to construct a citation index. By the early 1960s, this endeavor was supported by grants from the National Institutes of Health and the National Science Foundation. In November 1963, these efforts came to fruition, and the first edition of the SCI was published, covering citations in 1961 (Garfield, 1963b, see Figure A.1 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).[4]

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 by IBM computers (Garfield, 1963b, p. x (sic)). Entries were ordered by last names and initials of scientists (see Figure A.1). Figure 1 shows the 1961 entry for the medical scientist Murray Abell. His entry covers five cited papers: a 1950 paper in *Archives of Pathology* (vol. 50, p. 1), another 1950 paper in *Archives of Pathology* (vol. 50, p. 23), a 1956 paper in *Archives of Pathology* (vol. 61, p. 360), a 1957 paper in the *American Journal of Clinical Pathology* (vol. 28, p. 272), and a 1961 paper in *Cancer*

[3]Since we measure the information set of contemporaries in the 1960s, our analysis allows us to identify the effects of revealing new information on labor market outcomes. In this, we add to the literature on how information disclosure and new information technologies affect market efficiency (e.g., Jensen, 2007; Koudijs, 2015; Tadelis and Zettelmeyer, 2015; Steinwender, 2018; Bernstein et al., 2023).

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

(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.

Figure 1: Entry in the Science Citation Index

```
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
```

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

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

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

I.B Data

Reconstructing SCI Coverage from the Web of Science

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

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

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

covers both citations that were visible to contemporaries and citations that were invisible at the time, but became available during the backward expansions.

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

Faculty Rosters

To study how the introduction of citation metrics affects the careers of academics, we use data containing faculty rosters for nearly all universities in the United States from the *World of Academia Database* (see Iaria 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 biology, biochemistry, chemistry, physics, mathematics, or medicine. For the period of our analysis, the database provides the most comprehensive data on academics in the United States (see Iaria et al. (2022) for details). For the 1969 cross-section, the data contain 27,315 scientists at 1,477 departments in 384 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, which allows us to observe both academics who received citations and, importantly, academics who did not receive any citations. This enables us to construct comprehensive individual and department rankings based on *all* academics and not only based on those who published and were cited.

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) (see Appendix B.1.1 for details).

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

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

Table 1: Descriptive Statistics

Panel A: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Publications	8.75	16.65	0	405
Visible Citations	46.99	128.05	0	3,346
Invisible Citations	18.93	57.95	0	2,010
Full Professor Share	0.40	0.49		
Female Share	0.10	0.30		

Panel B: Number of Observations

Dataset includes:	Observations
Citations	1,800,669
Publications	239,124
Scientists	27,315
Departments	1,477
Universities	384

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

Constructing Scientist Rankings

Using 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), assigning 100 to the best and 1 to the worst scientist. This variable transformation allows us to compare the scientists' relative positions in the citation distributions, even if these distributions differ across subjects. For example, the median biologist received 2 citations, while the median chemist received 9 citations. If percentiles cannot be uniquely assigned because too many scientists have the same number of citations or publications, we assign the mid-point of the corresponding percentiles.[8] This is particularly important for scientists with zero citations. Alternative assignments of percentile ranks to scientists with zero citations do not affect our findings (see Appendix C.2.3).

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

[8]For example, in physics 30.37% of observations have zero citations. For the main results, we assign the mid-point between the 1st percentile and the 31st percentile, i.e., a percentile rank of 15.5, to each of these observations.

Constructing Department Rankings

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

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

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

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

While the SCI was predominantly designed to facilitate literature research, it was immediately used to evaluate scientists. For example, Eugene Garfield remembered:

> "The SCI's success did not stem from its primary function as a search engine, but from its use as an instrument for measuring scientific productivity." (Garfield, 2007, p. 65)

The eminent biologist Richard Dawkins described the SCI as a publication that:

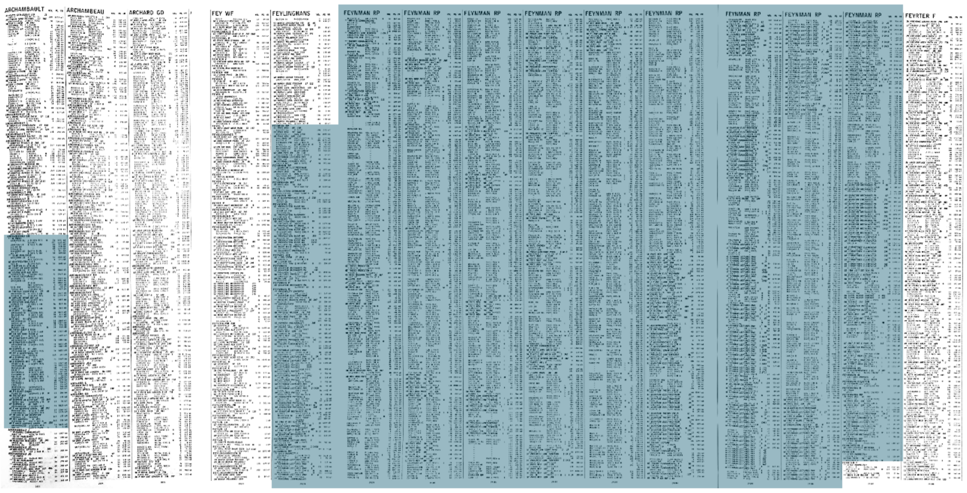
> "is intended as an aid to tracking down the literature on a given topic. University appointments committees have picked up the habit of using it as a rough

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

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 scientists. Figure 2 shows one such comparison for two scientists working at Caltech. The box on the left shows citations of the physicist Charles Archambeau. The box on the right shows the citations of the 1965 physics Nobel laureate Richard Feynman. As one contemporary remarked, "[a]n early form of research evaluation of individuals made use of a ruler to measure column inches of citations!" (Birkle et al., 2020, p. 364).

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 Caltech: Charles Archambeau on the left, and Nobel laureate Richard Feynman on the right.

Very quickly, scientists, funding bodies, and university administrators started to use citation counts in hiring, promotion, and funding decisions. Some universities even made citations a mandatory metric in the evaluation of applicants' portfolios (Wade, 1975, p. 429). The importance of newly available citation metrics is exemplified in the court case *Johnson v. University of Pittsburgh*.[10] In 1973, Sharon Johnson sued the biochemistry department at the University of Pittsburgh for sex discrimination. Her legal case argued that she was overlooked for tenure even though her papers had received more citations (as measured in the SCI) than those of two recently tenured male colleagues.

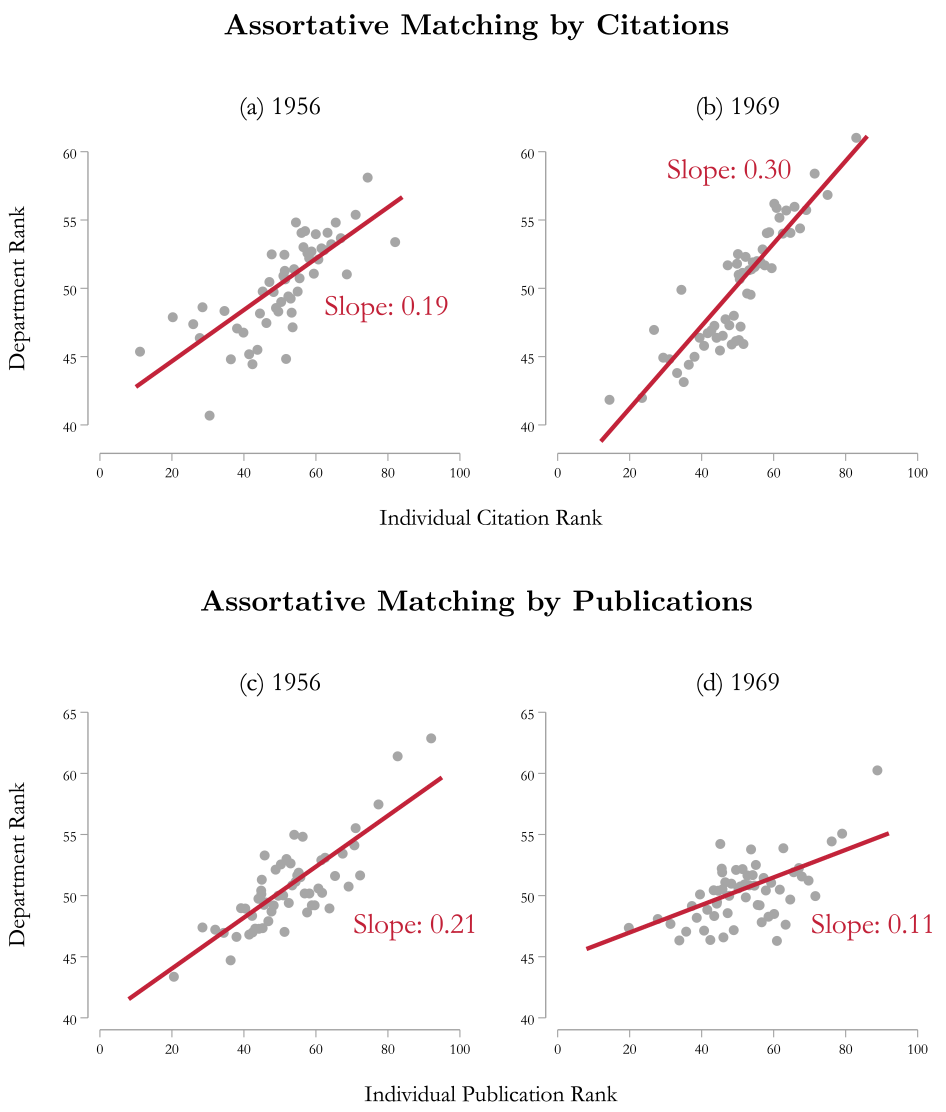
The SCI's Impact on Assortative Matching: Suggestive Evidence

We first provide suggestive evidence of the impact of the citation metrics on the assortative matching of academics and departments. If departments began to use the SCI to evaluate scientists, we would expect that the correlation between a scientist's citations and their department rank increased after the introduction of the SCI. We find that the correlation

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

between a scientist's individual citation rank and their department rank increased by 61% between 1956 and 1969 (Figure 3, panels (a) and (b)). In contrast, the correlation between the individual publication rank and the department rank decreased by 46% (Figure 3, panels (c) and (d)).

Figure 3: Assortative Matching Before and After Citation Metrics



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

This evidence is in line with the hypothesis that the introduction of citation metrics increased the reliance of hiring decisions on citations, and decreased the reliance on other observable characteristics such as publications. However, the increasing correlation between scientists' citation rank and their department rank may have been caused by other factors. For example, the increasing importance of expensive research labs or federal research funding (e.g., Kantor and Whalley, 2022) could disproportionately favor leading departments and allow them to attract highly cited scientists. 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.

II The Effect of Citation Metrics on Assortative Matching

II.A Empirical Strategy

We identify the causal effect of citation metrics by comparing the effect of citations that were *visible* in the SCI to the effect of citations that remained *invisible*. For technical reasons, the SCI only covered citations from 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 covered citations from 1961 in any of the 613 citing journals. As a result, all 1961 citations in those 613 journals became visible in the SCI, while citations before 1961 and in other journals remained invisible. Due to limited computing power, the collection of citation data was interrupted in 1962 and 1963. By 1964, data collection resumed. The set of indexed citing journals quickly expanded from 613 in 1961 to 2,180 in 1969. As a result, the visibility of citations was affected by two sources of variation: first, in which *year* a paper was cited, and second, in which *journal* it was cited.[11]

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

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

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

Table 2: Identifying Variation for Specification 1

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

Notes: This table reports citations of a hypothetical scientist's papers. Numbers in dark blue cells show citations that were visible in the SCI because the citation occurred in a journal and year (1961, or 1964-69) that was covered by the SCI. Numbers in light blue cells show citations that were invisible in the SCI, but are observable today.

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

Hence, if contemporaries had looked up the scientist's total citations in the SCI in 1969, they would have observed six citations, i.e., the scientist had six *visible* citations. In addition, the scientist had eight citations that were *invisible* at the time. Using modern citation data, we can observe both visible and invisible citations. For each scientist i, we separately count the number of visible and invisible citations between 1956 and 1969 to i's papers published between 1956 and 1969.

II.B Specification 1: Visible vs. Invisible Citations

Our identification strategy exploits the differential visibility of scientists' citations. If the very measurement of citations affects the assortativeness of the match between academics and universities, visible citations should be more predictive of career outcomes than invisible ones.[12] The identifying assumption underlying this new empirical strategy is that the effect of visible and invisible citations would be the same if both had been covered in the SCI. Given the arbitrary timing of the introduction of the SCI and the lack of coverage for the years 1962 and 1963, this seems plausible. Nonetheless, there may be concerns that any effect might be driven by differences in the quality of the citing journals or the timing of citations, i.e., by the two sources of variation in the visibility of citations. We address these concerns with alternative specifications outlined below.

We estimate the following regression:

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

where $\textit{Dep. Rank}_i$ is the department rank of scientist i in 1969, where 100 is the best and 1 the worst department.[13] $\textit{Visible Citations}_i$ measure scientist i's visible citations. $\textit{Invisible Citations}_i$ measure scientist i's invisible citations. In the baseline specification, we measure citations as the percentiles in the distributions of visible and invisible citations.[14] $\textit{Publications}_i$ flexibly control for scientists i's publications. $\textit{Subject FE}$ control for differences between academic subjects. To account for potential correlations of regression residuals in a certain department, e.g., in chemistry at Berkeley, we cluster all standard errors at the department-level.

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

[12] 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.

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

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

of the SCI, scientists will have an approximate idea about the importance and quality of other scientists' papers.

Table 3: Citations and Assortative Matching

	Dependent Variable: Department Rank				
	(1)	(2)	(3)	(4)	(5)
Specification 1: Visible vs. Invisible Citations					
Visible Citations	0.299	0.320	0.280	0.247	0.237
	(0.034)	(0.031)	(0.035)	(0.035)	(0.035)
Invisible Citations	0.103	0.068	0.062	0.061	0.060
	(0.023)	(0.020)	(0.021)	(0.023)	(0.024)
P-value (Visible = Invisible)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
R^2	0.138	0.140	0.153	0.232	0.261
Specification 2: Visible vs. Pseudo-Visible vs. Invisible Citations					
Visible Citations	0.305	0.327	0.284	0.252	0.243
	(0.035)	(0.032)	(0.036)	(0.035)	(0.036)
Pseudo-Visible Citations	0.033	0.012	0.013	0.028	0.022
	(0.021)	(0.020)	(0.020)	(0.022)	(0.023)
Invisible Citations (SCI years)	0.030	0.029	0.030	0.020	0.023
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Invisible Citations (non-SCI years)	0.057	0.044	0.037	0.025	0.029
	(0.017)	(0.016)	(0.016)	(0.016)	(0.017)
P-value (Visible = Pseudo-Visible)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
P-value (Visible = Invisible (SCI years))	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
P-value (Visible = Invisible (non-SCI years))	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
P-value (Pseudo-Vis. = Invis. (SCI) = Invis. (non-SCI))	0.451	0.551	0.676	0.941	0.956
R^2	0.138	0.141	0.154	0.232	0.261
Subject Fixed Effects	Yes	Yes	Yes	Yes	Yes
Publications by Year		Yes			
Publications by Year × Subject			Yes	Yes	Yes
Publications by Journal				Yes	
Publications by Journal × Subject					Yes
Observations	27,315	27,315	27,315	27,315	27,315
Dependent Variable Mean	50.40	50.40	50.40	50.40	50.40

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

We report estimates of Equation (1) in the first panel of Table 3. In column (1), we report a specification that controls for subject fixed effects. The coefficient for visible citations is around three times larger than the coefficient for invisible citations. Scientists with a 10 percentiles higher visible citation count were, on average, placed at a 3.0 percentiles higher-ranked department in 1969. For example, a chemist would be placed at Harvard or Stanford as opposed to Northwestern University or the University of Southern California. In contrast, scientists with a 10 percentiles higher invisible citation count were, on average, only placed at a 1.0 percentiles higher-ranked department.[15] We also report

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

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.

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.[16] One might be concerned that differences in publication and citation patterns across the sciences could explain our findings. For example, mathematicians publish fewer papers and receive fewer citations than chemists or medical researchers. To address this concern, we show that the results are robust to separately controlling for the number of publications by year and subject (column (3)).

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

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

Alternative Explanation 1: Quality of Citing Journals

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

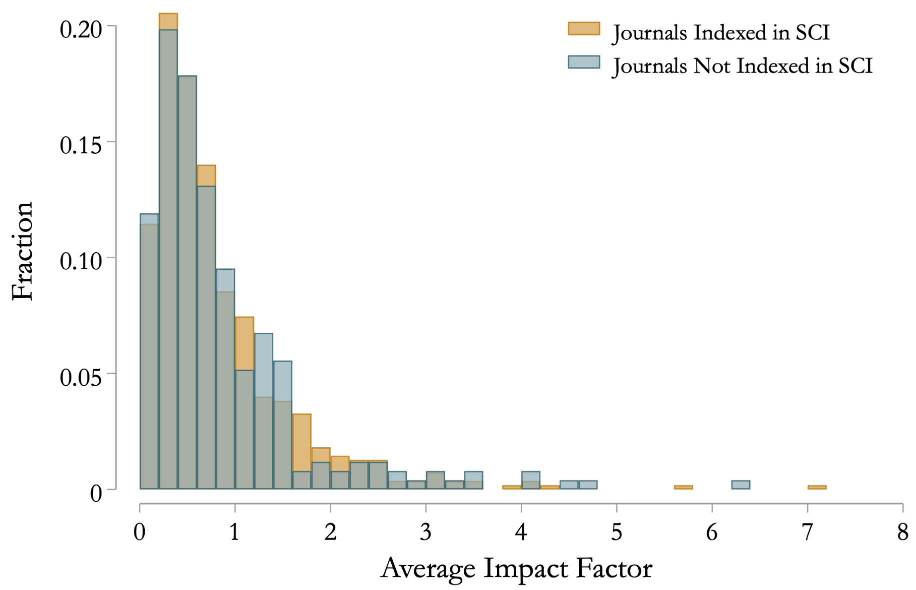
The first concern is that visible citations may come from citing articles in higher quality journals (e.g., *Nature* or *Science*) and therefore have a larger impact on a scientist's career. It is important to note that this concern is somewhat mitigated because it was difficult to assess journal quality before the introduction of the SCI. Some of the citing journals initially indexed in the SCI turned out to be of relatively lower quality. Similarly,

[16]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.

many journals that were, in fact, of high quality were not indexed during the first years of the SCI.

While it was not possible to quantitatively measure journal quality at the time, we can retrospectively compute measures of the quality of the citing journal and thereby assess whether visible citations came from better journals. For this test, we compute the impact factors for all citing journals in the pre-SCI period.[17] Journals which were indexed in the 1961 SCI had an average impact factor of 0.83, while journals which were not indexed had an average impact factor of 0.86 (p-value of test of equal means: 0.618). We also plot the distributions of the average impact factors for both types of journal in Figure 4. This analysis indicates that journals indexed in the 1961 volume of the SCI were not of higher quality than journals that were not indexed.

Figure 4: Quality of Journals Indexed and Not Indexed in SCI



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

To provide additional evidence that differences in the quality of citing journals are not driving the results, we estimate regressions that only consider citations from a fixed set of journals. For this test, we only rely on 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).[18]

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

[18]We visualize the underlying variation of this robustness check in panel (b) of Appendix Figure C.2.

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

Alternative Explanation 2: Timing of Citations

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

We address this concern by fixing the timing of citations and exclusively relying on across-journal variation in visibility. In particular, we estimate regressions that only use visible and invisible citations from years in which the SCI was available (i.e., 1961 and 1964-1969). This exercise compares scientists with the same publication record who were cited in similar years but in different journals, only some of which were covered in the SCI.[19]

For our hypothetical scientist presented in Table 2, this test considers six visible citations: one from journal A in 1961, two from journal A in 1967, and three from journal B in 1966. It also considers three invisible citations: one each from journal B in 1961 and 1965, and one from journal C in 1969.[20]

The results that use only citations from years in which the SCI was published are very similar to the main results (Appendix Table C.7). 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.[21]

[19] 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.

[20] See also panel (c) of Appendix Figure C.2.

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

II.C Specification 2: Visible vs. Pseudo-Visible vs. Invisible Citations

The quality of citing journals and the timing of citations might interact to make visible citations more predictive for assortative matching. To address such concerns, we introduce a second specification, which includes a placebo test that compares the predictiveness of different types of invisible citations. For this specification, we partition the citation space into four mutually exclusive sets depending on where and when a scientist was cited (see Table 4):

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

2. *Pseudo-visible citations*: citations from journals that were indexed in the SCI in 1961 but from years when the SCI was not published (1956-1960 and 1962-1963),

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

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

Table 4: Identifying Variation for Specification 2

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

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

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

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

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

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 $\delta_1 \gg \delta_2 \approx \theta_1 \approx \theta_2$. Note that the comparison between visible and pseudo-visible citations allows us to estimate the causal effect of citation metrics even if journals indexed in the SCI differed in quality from journals not indexed in the SCI.

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

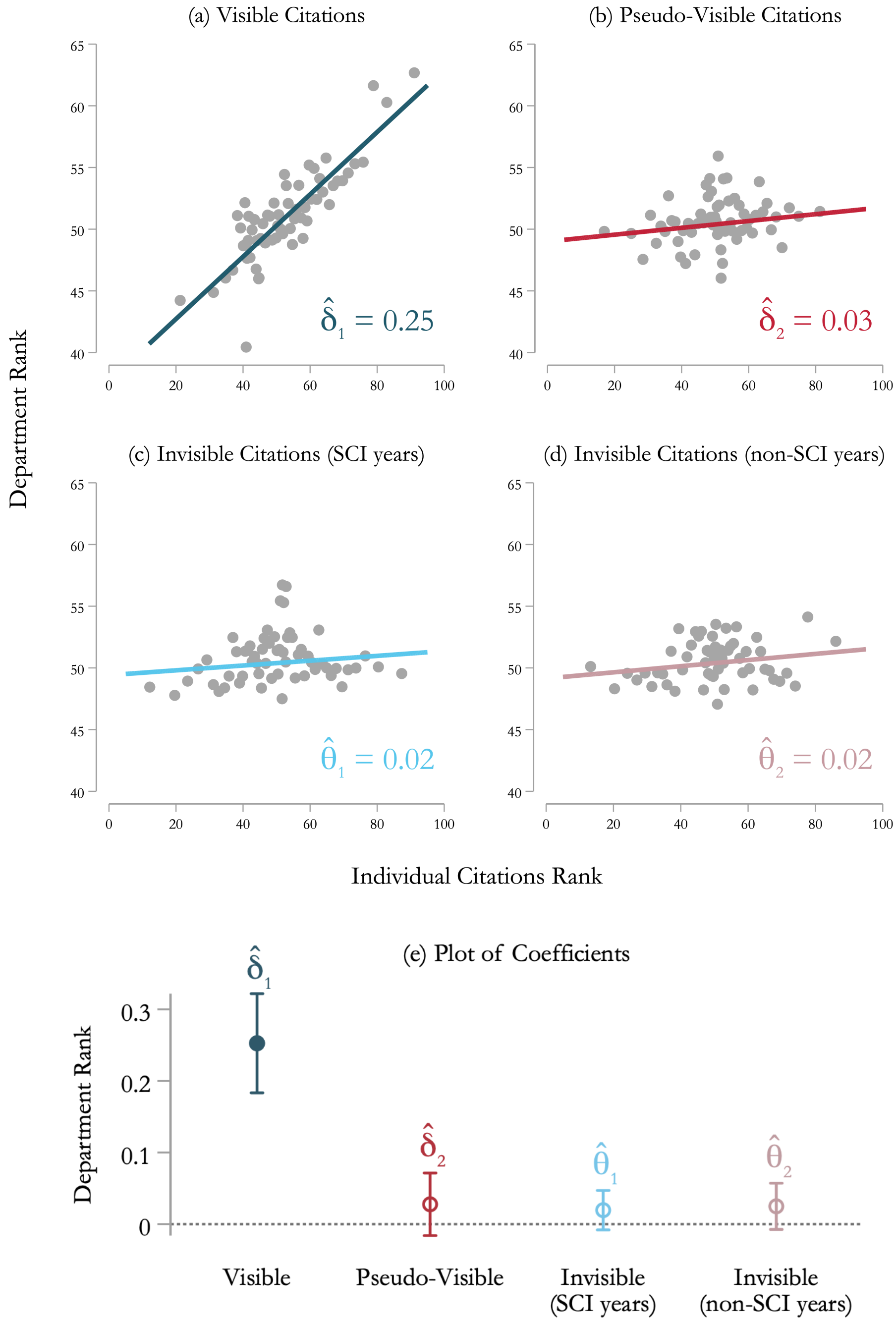
II.D Mechanisms

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

Effect on Leaving Academia

We start by estimating the impact of citation metrics on the probability of leaving academia. For these regressions, we study scientists who we observe in the 1956 cross-section of academics. We exclude scientists who were already full professors in 1956 to avoid picking

Figure 5: Assortative Matching, Specification 2



Notes: The figure illustrates the results from Equation (2), see Table 3, Specification 2. Panels (a) to (d) report bin-scatter plots illustrating the relationship between citation ranks and the department rank. Panel (e) plots the coefficients and 95 percent confidence intervals.

up retirements.[22] We then check whether these scientists had left academia by 1969. We estimate the following regressions:

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

Specification 1:

$$\mathbb{1}[Leaving\ Academia]_i = \delta \cdot Visible\,Citations_i + \theta \cdot Invisible\,Citations_i \\ + \pi \cdot Publications_i + Subject\,FE + \epsilon_i \tag{3}$$

Specification 2:

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

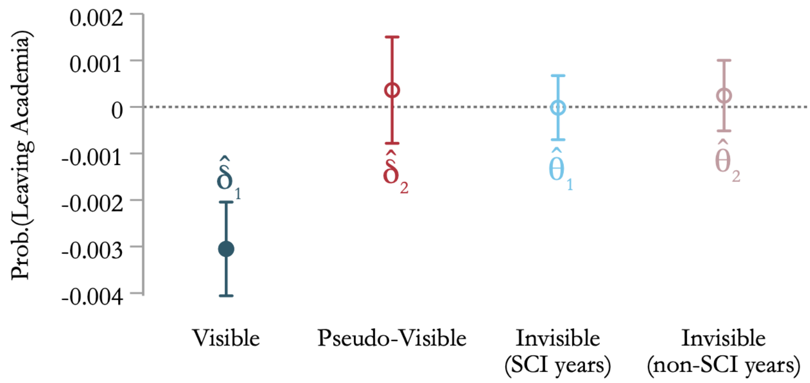
where $\mathbb{1}[Leaving\ Academia]_i$ is an indicator variable equal to one if a scientist left academia between 1956 and 1969. The remaining variable definitions are identical to the definitions in Equations (1) and (2).

Table 5: Mechanism 1: Leaving Academia

	Dependent Variable: Leaving Academia				
	(1)	(2)	(3)	(4)	(5)
Specification 1: Visible vs. Invisible Citations					
Citations Visible	-0.0038	-0.0042	-0.0038	-0.0034	-0.0033
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Citations Invisible	0.0001	0.0008	0.0009	0.0010	0.0009
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
P-value (Visible = Invisible)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
R^2	0.088	0.092	0.105	0.244	0.297
Specification 2: Visible vs. Pseudo-Visible vs. Invisible Citations					
Visible Citations	-0.0037	-0.0039	-0.0035	-0.0031	-0.0031
	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Pseudo-Visible Citations	0.0002	0.0006	0.0006	0.0004	0.0004
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0006)
Invisible Citations (SCI years)	-0.0002	-0.0000	0.0000	-0.0000	-0.0001
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Invisible Citations (non-SCI years)	-0.0000	0.0001	0.0001	0.0002	0.0005
	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
P-value (Visible = Pseudo-Visible)	< 0.001	< 0.001	< 0.001	0.001	0.001
P-value (Visible = Invisible (SCI years))	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
P-value (Visible = Invisible (non-SCI years))	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
P-value (Pseudo-Vis. = Invis. (SCI) = Invis. (non-SCI))	0.718	0.510	0.579	0.810	0.521
R^2	0.089	0.092	0.105	0.244	0.297
Subject Fixed Effects	Yes	Yes	Yes	Yes	Yes
Publications by Year		Yes			
Publications by Year × Subject			Yes	Yes	Yes
Publications by Journal				Yes	
Publications by Journal × Subject					Yes
Observations	12,368	12,368	12,368	12,368	12,368
Dependent Variable Mean	0.691	0.691	0.691	0.691	0.691

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

Figure 6: Leaving Academia, Specification 2



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

The probability of leaving academia was lower for academics with a higher visible citation count (Table 5, Specification 1). Scientists with a 10 percentile higher visible citation count were around 3.4 percentage points (or 5.0 percent relative to the mean) less likely to leave academia between 1956 and 1969. Strikingly, invisible citations did not have a significant impact on the probability of leaving academia. The p-values for the tests that the coefficients on visible and invisible citations are equal are lower than 0.001. The estimates from Specification 2 confirm these findings (Table 5, Specification 2; and Figure 6). These results suggest that the increased assortative matching of academics was, in part, driven by scientists with fewer visible citations leaving academia.

Effect on Moving to a Higher-Ranked Department

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

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

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

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

	Dep. Var.: Moving to Higher-Ranked Department				
	(1)	(2)	(3)	(4)	(5)
Specification 1: Visible vs. Invisible Citations					
Visible Citations	0.0008	0.0007	0.0006	0.0008	0.0007
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Invisible Citations	-0.0001	0.0001	0.0000	-0.0003	-0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
P-value (Visible = Invisible)	0.101	0.254	0.238	0.078	0.154
R^2	0.014	0.018	0.037	0.336	0.405
Specification 2: Visible vs. Pseudo-Visible vs. Invisible Citations					
Visible Citations	0.0008	0.0007	0.0006	0.0007	0.0006
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Pseudo-Visible Citations	-0.0002	-0.0001	-0.0002	-0.0004	-0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0004)
Invisible Citations (SCI years)	0.0002	0.0002	0.0002	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Invisible Citations (non-SCI years)	-0.0000	0.0000	0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
P-value (Visible = Pseudo-Visible)	0.027	0.076	0.076	0.059	0.147
P-value (Visible = Invisible (SCI years))	0.113	0.189	0.252	0.271	0.358
P-value (Visible = Invisible (non-SCI years))	0.015	0.050	0.102	0.134	0.281
P-value (Pseudo-Vis. = Invis. (SCI) = Invis. (non-SCI))	0.498	0.625	0.519	0.389	0.564
R^2	0.014	0.018	0.037	0.336	0.405
Subject Fixed Effects	Yes	Yes	Yes	Yes	Yes
Publications by Year		Yes			
Publications by Year × Subject			Yes	Yes	Yes
Publications by Journal				Yes	
Publications by Journal × Subject					Yes
Observations	6,478	6,478	6,478	6,478	6,478
Dependent Variable Mean	0.046	0.046	0.046	0.046	0.046

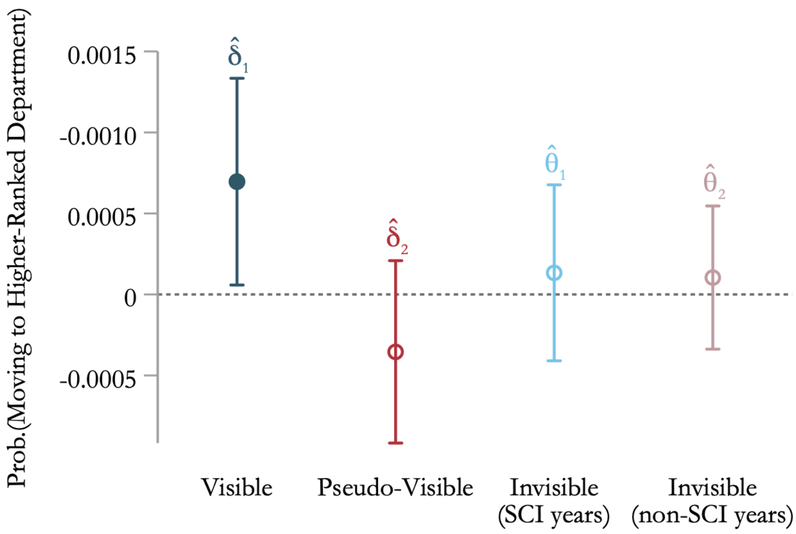
Notes: The table reports the estimates of variants of Equations (3) and (4) with a different dependent variable: an indicator equal to one if scientist i moved to a higher-ranked department between 1956 and 1969. These regressions use the sample of scientists observed in 1956 and 1969. The explanatory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

II.E Overcoming Information Frictions Across Geographic and Intellectual Distance

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

We first investigate whether citation metrics help to overcome information frictions due to geographic distance. Specifically, we estimate two regressions with different dependent variables: (1) an indicator equal to 1 if scientist i moved to a higher-ranked department that was geographically far, and (2) an indicator equal to 1 if scientist i moved to a higher-ranked department that was geographically close. We define departments to be

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



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

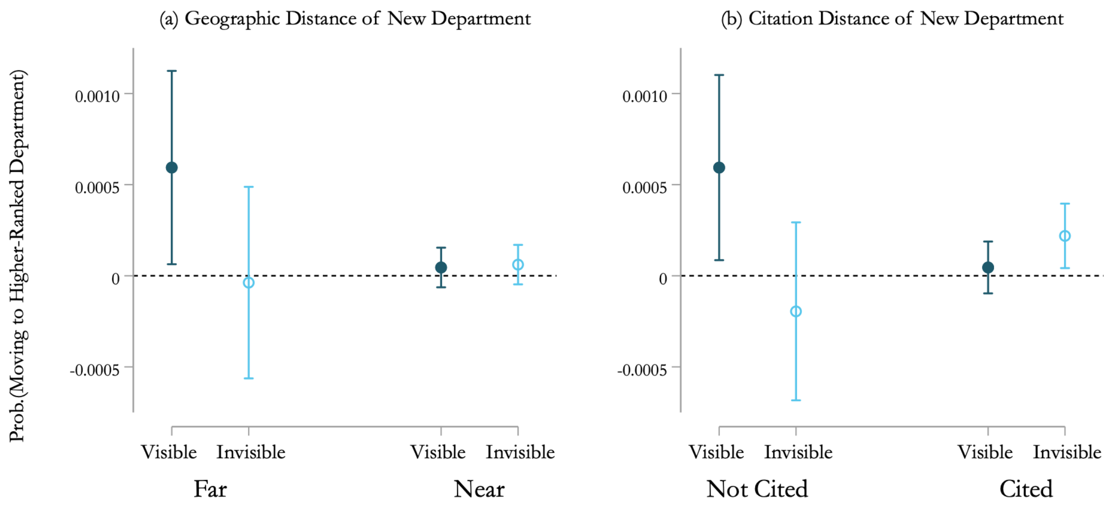
geographically far if they are more than 100km apart.[23] The results suggest that citation metrics only impacted moves to higher-ranked departments that were geographically far but not to departments that were geographically close (Figure 8, panel (a); and Table C.10). We also investigate whether citation metrics helped to overcome information frictions due to intellectual distance. We measure intellectual distance using cross-department citations before the move of the scientist. Specifically, we measure whether scientist i's papers had been cited in the receiving department before the introduction of the SCI in 1963. We estimate two regressions with alternative dependent variables: (1) an indicator equal to 1 if scientist i moved to a higher-ranked department where i's research was not cited before the move, and (2) an indicator equal to one if scientist i moved to a higher-ranked department where i's research was cited at least once before the move.[24] The results suggest that citation metrics only impacted moves to higher-ranked departments where scientist i had not been cited before the move (Figure 8, Panel B; and Table C.10).

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

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

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

Figure 8: Moving To Higher-Ranked Departments by Geographic and Intellectual Distance



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

III Heterogeneous Impact of Performance Metrics

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

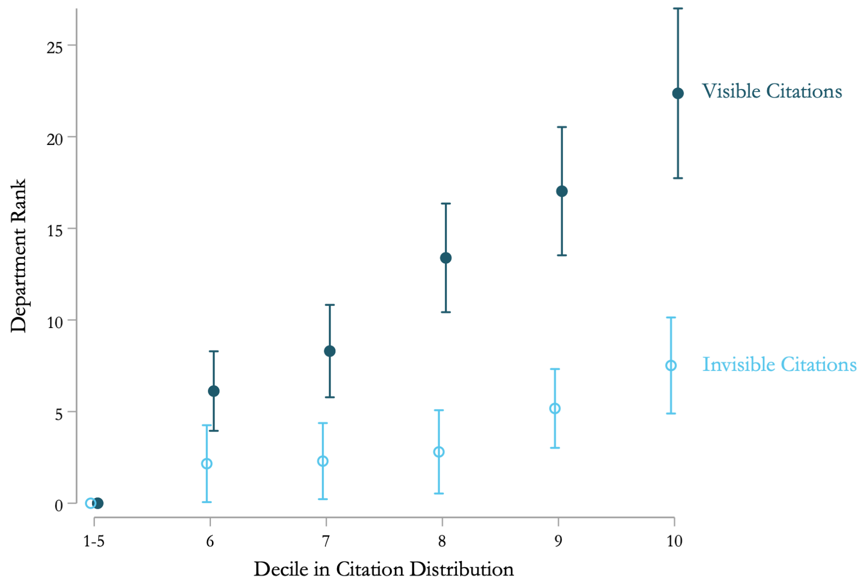
III.A Heterogeneous Effects by Individual-Level Citation Rank

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

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

$\mathbb{1}(Visible\ Cit\ Decile_i = q)$ and $\mathbb{1}(Invisible\ Cit\ Decile_i = q)$ are indicator variables for i's decile in the visible and invisible citation distributions, respectively. We visualize the estimates relative to the bottom half of the visible and invisible individual-level citation distribution (Figure 9).[25]

Figure 9: Heterogenous Effects by Individual-Level Citation Rank



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

Over the upper half of the citation distribution, an increase in visible citations increases the assortativeness of the match between the rank of scientist i and the rank of her department. Furthermore, the gap between visible and invisible citations widens for higher deciles of the citation distribution. A scientist in the top decile of the visible citation distribution was, on average, placed in a department that was 22.4 percentiles higher in the department ranking, compared to scientists in the bottom half of the visible citation distribution. This is equivalent to a physicist being placed at Harvard as opposed to Case Western Reserve University. In contrast, a scientist in the top decile of the invisible citation distribution was, on average, placed in a department that was only seven percentiles higher ranked, compared to a scientist in the bottom half of the invisible citation distribution. In 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.

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

III.B Heterogeneous Effects for Peripheral Scientists

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

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

Variable definitions are identical to Equation (5). We add interactions between the deciles of the individual-level citation distributions with indicator variables that equal one if the scientist was working in either a high-ranked or a low-ranked department in 1956. We also control for the main effect of working in a low-ranked department in 1956. We define low-ranked departments as those below the 75th percentile of the department ranking.[26] In physics, for example, low-ranked departments are all departments that were ranked lower than the University of Wisconsin, Madison.

We show estimates for the deciles of the visible citation distribution for scientists in high-ranked and low-ranked departments in Figure 10.[27] Estimates for scientists in low-ranked departments are consistently larger than for scientists in high-ranked departments. The p-values for the tests that coefficients for the top two deciles are the same in low-ranked and high-ranked departments are below 0.001. This indicates that scientists who were in lower-ranked departments in 1956 benefited disproportionately from the availability of citation metrics.[28]

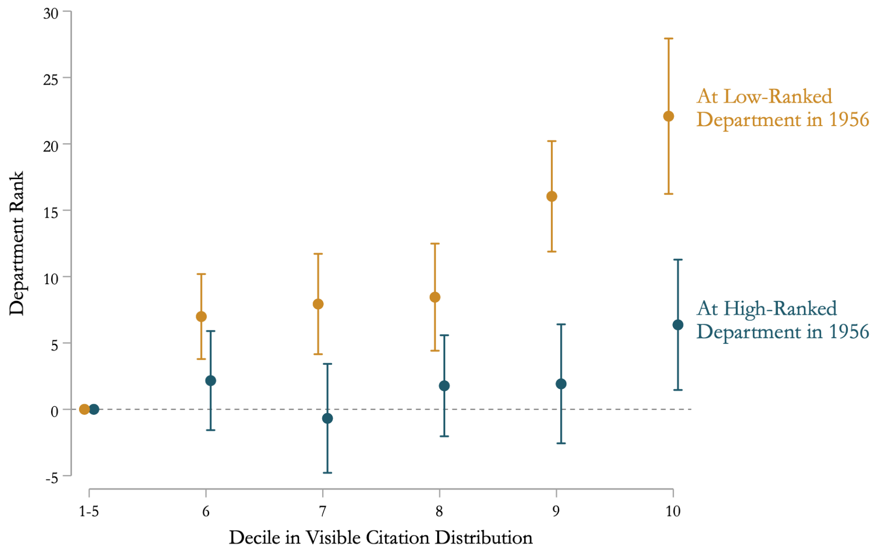
In other words, citation metrics enabled the discovery of "hidden stars." This may have reduced misallocation by helping the highest-cited scientists in low-ranked departments to move to high-ranked departments. This finding is consistent with anecdotal evidence; for example, a contemporary scientist remarked that "[t]he SCI was especially useful to find people who would otherwise be overlooked" (as cited in Wouters, 1999b, p. 138).

[26] Results are qualitatively similar if we use alternative cutoffs (e.g., 60th, 70th, 80th, or 90th percentile, see Appendix Figure D.2).

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

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

Figure 10: Heterogenous Effect of Citation Rank for Peripheral Scientists



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

One example, of such a "hidden star" is the medical scientist Hans Hecht. Swiss-born, he obtained his M.D. in Germany in 1936. He escaped the Nazi regime in 1938 and emigrated to the United States.[29] He started his U.S. career as an "Instructor of Medicine at the Wayne University School of Medicine, following which he moved to the University of Utah, where, in 1946, he earned a second M.D. degree" (Katz, 1971) and became a professor there. Arnold Katz of the Mount Sinai School of Medicine described that his: "breadth of scientific interests [...] was always based on an extraordinarily high level of scientific excellence [...] he was never taken in by the investigator with a long list of unoriginal or superficial papers, but saw clearly the essential quality of a man's work" (Katz, 1971). In the mid-1960s, Hans Hecht was hired by the University of Chicago.

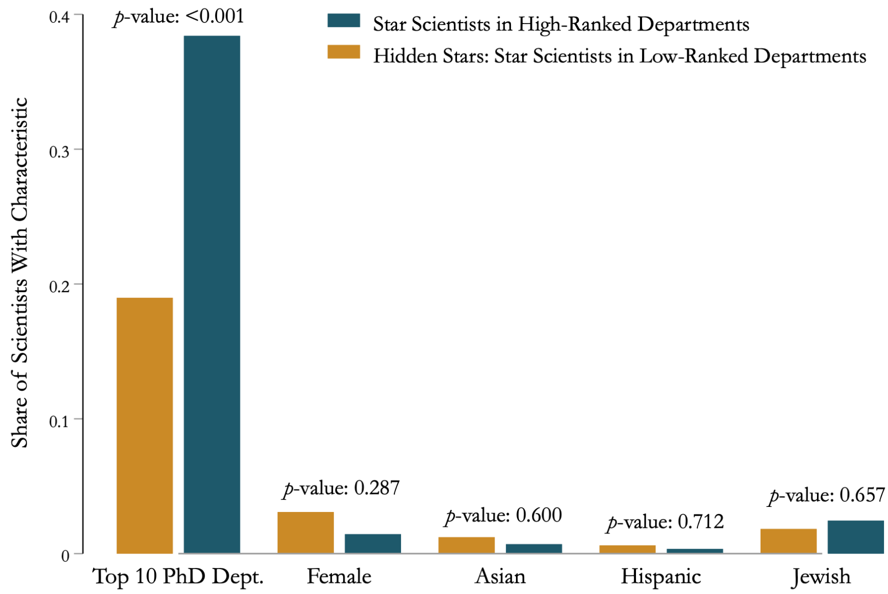
We explore whether the example of Hans Hecht indeed provides more general insights into the characteristics of "hidden stars." That is, we investigate which characteristics are correlated with being underplaced before the availability of citation metrics. For this analysis, we define star scientists as scientists whose total citations (both visible and invisible) place them in the top five percent of the subject-level citation distribution in 1969. For these 450 scientists we can infer some characteristics from our data, e.g., whether they were female, but also whether they were of Asian, Hispanic, or Jewish origin. We measure these characteristics based on the names of academics (for more details, see Appendix B.1). In addition, we collect information on where these star scientists obtained their Ph.D. through an extensive web search.[30]

We then report the average characteristics of star scientists in high-ranked departments

[29]See Becker et al. 2023 for the emigration of scientists from Nazi Germany.
[30]We obtain the Ph.D. university for 400 out of the 450 star scientists.

and of star scientists who worked in low-ranked departments in 1956 ("hidden stars"). 38% of star scientists in high-ranked departments had received a Ph.D. from a top-10 department in the United States. In contrast, only 18% of "hidden stars" had received a Ph.D. from a top-10 department (Figure 11). We also find that there were twice as many women among "hidden stars". Since there were very few women in academia at the time (Iaria et al., 2022), the difference is not statistically significant. Overall, this evidence suggests that "hidden stars" had, on average, obtained their Ph.D. from worse universities and that they were more likely to be female.

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



Notes: The figure reports characteristics of star scientists who were in high-ranked departments (blue) and low-ranked departments ("hidden stars," orange) in 1956. As before, low-ranked departments are those below the 75th percentile of the department ranking in 1956. For this figure, we define star scientists as all scientists in the top five percent of the subject-level citation distribution.

III.C Heterogeneous Effects for Minority Scientists

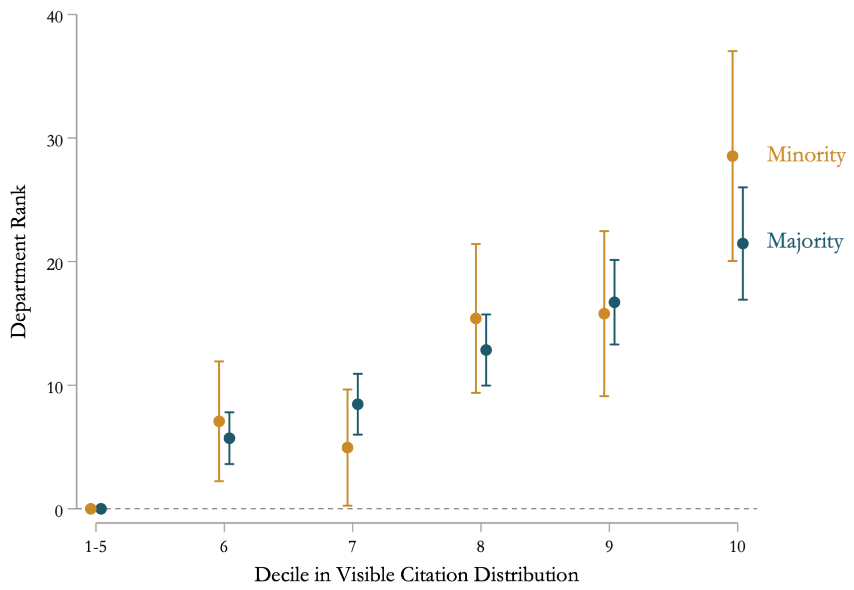
In the last part of this section, we investigate the heterogeneous impacts of citation metrics on minority scientists. Specifically, we analyze whether women, Hispanics, Asians, and Jews disproportionately benefited from the availability of citation metrics. As outlined above, we identify these groups based on the names of academics. As the proportion of minorities among academics was low in the 1960s (e.g., Card et al. 2023, Iaria et al. 2022), we pool all minorities to gain power. We then estimate the following regression:

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

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

While we do not find evidence that minority scientists, on average, benefited more from citation metrics than majority scientists (Appendix Table D.2), the evidence in Figure 12 suggests that among star scientists (top decile) minority scientists benefit slightly more than majority scientists.[31] The p-value for the test that the coefficients for the tenth decile are the same for minority and majority scientists is 0.051.

Figure 12: Heterogenous Effects for Majority and Minority Scientists



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

Taken together, these results suggest that the availability of more "objective" performance metrics helped disadvantaged high-quality scientists. In particular, highly cited

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

scientists in lower-ranked departments ("hidden stars") and highly cited minority scientists benefited from the availability of citation metrics.

IV Impact of Performance Metrics on Careers

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

Specification 1:

$$\begin{aligned}\mathbb{1}[CareerOutcome]_i = \delta \cdot Visible\,Citations_i + \theta \cdot Invisible\,Citations_i \\ + \pi \cdot Publications_i + Subject\,FE + \epsilon_i\end{aligned} \tag{8}$$

Specification 2:

$$\begin{aligned}\mathbb{1}[CareerOutcome]_i = {} & \delta_1 \cdot Visible\,Citations_i + \delta_2 \cdot Pseudo\text{-}Visible\,Citations_i \\ & + \theta_1 \cdot Invisible\,Citations\,(SCI\,years)_i + \theta_2 \cdot Invisible\,Citations\,(non\text{-}SCI\,years)_i \\ & + \pi \cdot Publications_i + Subject\,FE + \epsilon_i\end{aligned} \tag{9}$$

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

IV.A Effect on Promotions

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 and peer recognition. We estimate Equations (8) and (9), where the dependent variable equals one if scientist i was promoted to full professor between 1956 and 1969.

We find that the visible citation rank has a significant positive impact on promotions (Table 7). The probability of promotion increased by 4.1 percentage points (or 5.8 percent relative to the mean) for scientists with a 10 percentile higher visible citation rank.[32]

[32] 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 II.D), we likely estimate a lower-bound of the effect of citation metrics on promotions.

The estimates for invisible citations are close to zero and statistically insignificant. The estimates from Specification 2 confirm these findings (Table 7 and Figure 13, panel (a)).

Table 7: Promotion to Full Professor

	Dependent Variable: Promotion to Full Professor				
	(1)	(2)	(3)	(4)	(5)
Specification 1: Visible vs. Invisible Citations					
Visible Citations	0.0042	0.0046	0.0047	0.0041	0.0040
	(0.0006)	(0.0007)	(0.0007)	(0.0010)	(0.0013)
Invisible Citations	0.0009	0.0003	0.0004	-0.0003	-0.0001
	(0.0005)	(0.0006)	(0.0006)	(0.0010)	(0.0012)
P-value (Visible = Invisible)	0.002	< 0.001	< 0.001	0.017	0.068
R^2	0.140	0.145	0.154	0.366	0.395
Specification 2: Visible vs. Pseudo-Visible vs. Invisible Citations					
Visible Citations	0.0043	0.0048	0.0048	0.0041	0.0041
	(0.0006)	(0.0006)	(0.0007)	(0.0010)	(0.0013)
Pseudo-Visible Citations	0.0000	-0.0004	-0.0003	-0.0002	0.0001
	(0.0006)	(0.0006)	(0.0006)	(0.0011)	(0.0012)
Invisible Citations (SCI years)	0.0006	0.0005	0.0005	0.0006	0.0006
	(0.0005)	(0.0005)	(0.0005)	(0.0009)	(0.0011)
Invisible Citations (non-SCI years)	0.0003	0.0001	0.0002	-0.0007	-0.0011
	(0.0005)	(0.0005)	(0.0005)	(0.0009)	(0.0011)
P-value (Visible = Pseudo-Visible)	< 0.001	< 0.001	< 0.001	0.017	0.068
P-value (Visible = Invisible (SCI years))	< 0.001	< 0.001	< 0.001	0.015	0.054
P-value (Visible = Invisible (non-SCI years))	< 0.001	< 0.001	< 0.001	< 0.001	0.002
P-value (Pseudo-Vis. = Invis. (SCI) = Invis. (non-SCI))	0.755	0.541	0.663	0.678	0.655
R^2	0.140	0.146	0.154	0.366	0.395
Subject Fixed Effects	Yes	Yes	Yes	Yes	Yes
Publications by Year		Yes			
Publications by Year × Subject			Yes	Yes	Yes
Publications by Journal				Yes	
Publications by Journal × Subject					Yes
Observations	3,364	3,364	3,364	3,364	3,364
Dependent Variable Mean	0.707	0.707	0.707	0.707	0.707

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

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

IV.B Effect on Research Grants

Finally, we investigate the effect of citation metrics on receiving research grants. This analysis examines whether citation metrics affect the allocation of resources and recognition by the wider scientific community. We digitize entries of all grants awarded in 1969 by the National Science Foundation (NSF) and match them to the scientists in our faculty rosters (see Appendix B.1.3). We estimate Equations (8) and (9), where the dependent variable equals one if scientist i received at least one NSF grant.[33]

Table 8: Receiving an NSF Grant

	Dependent Variable: Receiving NSF Grant				
	(1)	(2)	(3)	(4)	(5)
Specification 1: Visible vs. Invisible Citations					
Visible Citations	0.0021	0.0017	0.0015	0.0013	0.0012
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Invisible Citations	0.0003	-0.0000	-0.0000	0.0001	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
P-value (Visible = Invisible)	< 0.001	< 0.001	< 0.001	0.001	0.002
R^2	0.064	0.070	0.086	0.215	0.249
Specification 2: Visible vs. Pseudo-Visible vs. Invisible Citations					
Visible Citations	0.0020	0.0017	0.0015	0.0012	0.0012
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Pseudo-Visible Citations	-0.0004	-0.0005	-0.0005	-0.0002	-0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Invisible Citations (SCI years)	0.0003	0.0001	0.0003	0.0003	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Invisible Citations (non-SCI years)	0.0007	0.0005	0.0005	0.0004	0.0005
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
P-value (Visible = Pseudo-Visible)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
P-value (Visible = Invisible (SCI))	< 0.001	< 0.001	< 0.001	0.001	0.003
P-value (Visible = Invisible (non-SCI))	< 0.001	< 0.001	0.002	0.009	0.022
P-value (Pseudo-Vis. = Invis. (SCI) = Invis. (non-SCI))	0.005	0.016	0.005	0.200	0.222
R^2	0.066	0.071	0.087	0.215	0.249
Subject Fixed Effects	Yes	Yes	Yes	Yes	Yes
Publications by Year		Yes			
Publications by Year × Subject			Yes	Yes	Yes
Publications by Journal				Yes	
Publications by Journal × Subject					Yes
Observations	15,582	15,582	15,582	15,582	15,582
Dependent Variable Mean	0.068	0.068	0.068	0.068	0.068

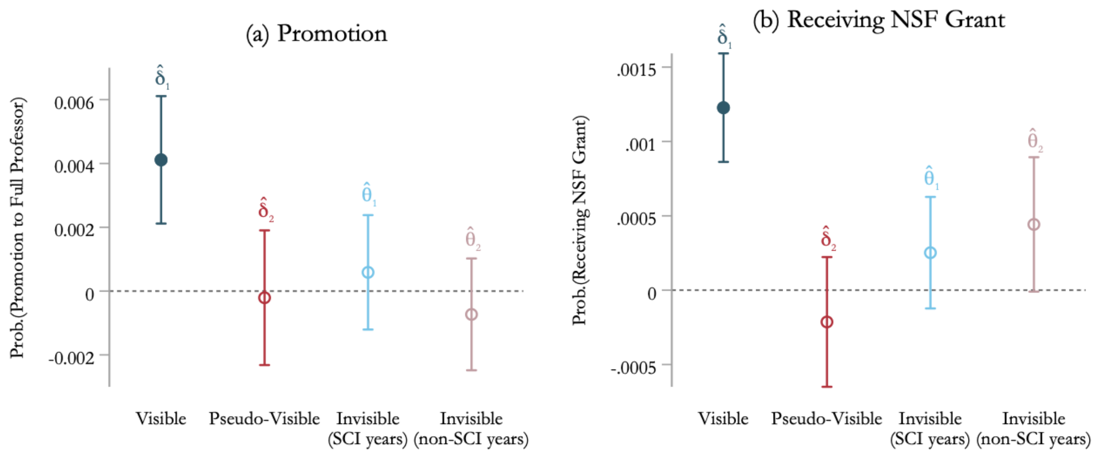
Notes: The table reports the estimates of Equation (8) in the first panel and of Equation (9) in the second panel. The dependent variable is an indicator equal to one if scientist i received an NSF grant in 1969. These regressions use the sample of scientists observed in 1969, excluding medicine. The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

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

These results highlight that the effects of citation metrics go beyond the allocation of talent: they affect whether scientists are promoted and whether they receive research

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

Figure 13: Effect on Career Outcomes, Specification 2



Notes: The figure plots coefficients and 95 percent confidence intervals from variants of Equation (9), see Tables 7 and 8, Specification 2.

grants. Thus, recognition through citations enables high-performing scientists to accrue additional rewards and resources, contributing to Matthew effects in the sciences (Merton, 1968).

V Conclusion

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

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

References

Abowd, J. M., F. Kramarz, and D. N. Margolis (1999). High Wage Workers and High Wage Firms. *Econometrica 67*(2), 251–333.

Andrews, M. J., L. Gill, T. Schank, and R. Upward (2008). High Wage Workers and Low Wage Firms: Negative Assortative Matching or Limited Mobility Bias? *Journal of the Royal Statistical Society: Series A (Statistics in Society) 171*(3), 673–697.

Azoulay, P., C. Fons-Rosen, and J. S. G. Zivin (2019). Does Science Advance one Funeral at a Time? *American Economic Review 109*(8), 2889–2920.

Azoulay, P., J. S. Graff Zivin, and J. Wang (2010). Superstar Extinction. *Quarterly Journal of Economics 125*(2), 549–589.

Azoulay, P., T. Stuart, and Y. Wang (2014). Matthew: Effect or Fable? *Management Science 60*(1), 92–109.

Becker, S. O., V. Lindenthal, S. Mukand, and F. Waldinger (2023). Scholars at Risk: Professional Networks and High-Skilled Emigration from Nazi Germany. *American Economic Journal: Applied Economics*.

Benetti, S., E. Locke, and R. Mattheis (2023). Our Crowd: Discrimination and Identity in Jewish Migration to the US. *Working Paper*.

Bernstein, A., C. Frydman, and E. Hilt (2023). The Value of Ratings: Evidence from their Introduction in Securities Markets. *NBER Working Paper 31064*.

Biagioli, M. and A. Lippman (2020). *Gaming the Metrics: Misconduct and Manipulation in Academic Research.* Cambridge: MIT Press.

Birkle, C., D. A. Pendlebury, J. Schnell, and J. Adams (2020). Web of Science as a Data Source for Research on Scientific and Scholarly Activity. *Quantitative Science Studies 1*(1), 363–376.

Borjas, G. J. and K. B. Doran (2012). The Collapse of the Soviet Union and the Productivity of American Mathematicians. *The Quarterly Journal of Economics 127*(3), 1143–1203.

Card, D. and S. DellaVigna (2020). What do Editors Maximize? Evidence from Four Economics Journals. *Review of Economics and Statistics 102*(1), 195–217.

Card, D., S. DellaVigna, P. Funk, and N. Iriberri (2020). Are Referees and Editors in Economics Gender Neutral? *The Quarterly Journal of Economics 135*(1), 269–327.

Card, D., S. DellaVigna, P. Funk, and N. Iriberri (2022). Gender Differences in Peer Recognition by Economists. *Econometrica 90*(5), 1937–1971.

Card, D., S. DellaVigna, P. Funk, and N. Iriberri (2023). Gender Gaps at the Academies. *Proceedings of the National Academy of Sciences 120*(4).

Card, D., J. Heining, and P. Kline (2013). Workplace Heterogeneity and the Rise of West German Wage Inequality. *The Quarterly Journal of Economics 128*(3), 967–1015.

Cartter, A. M. (1966). *An Assessment of Quality in Graduate Education.*

Charlton, L. (1981, April 26). An Index to Getting Ahead. *The New York Times*, 48.

CoARA (2022). Coalition for Advancing Research Assessment. https://coara.eu/.

Cole, J. R. and J. A. Lipton (1977). The Reputations of American Medical Schools. *Social Forces 55*(3), 662–684.

Csiszar, A. (2017). The catalogue that made metrics, and changed science. *Nature 551*(7679), 163–165.

Dawkins, R. (1986). *The Selfish Gene*. Oxford: Oxford University Press.

DORA (2013). San Francisco Declaration on Research Assessment. https://sfdora.org/.

Ellison, G. (2013). How does the Market use Citation Data? The Hirsch Index in Economics. *American Economic Journal: Applied Economics 5*(3), 63–90.

Feltham, G. A. and J. Xie (1994). Performance Measure Congruity and Diversity in Multi-Task Principal/Agent Relations. *The Accounting Review 69*, 429–453.

Floyd, E., S. Tomar, and D. Lee (2022). Making the Grade (But Not Disclosing It): How Withholding Grades Affects Student Behavior and Employment. *Available at SSRN 4097763*.

Forbes (2013). Big Data in Human Resources: Talent Analytics (People Analytics) Comes of Age. `https://www.forbes.com/sites/joshbersin/2013/02/17/bigdata-in-human-resources-talent-analytics-comes-of-age/?sh=7ae9b80a4cd0`, Last accessed on 2023-04-18.

Garfield, E. (1963a). Citation Indexes in Sociological and Historical Research. *American Documentation 14*(4), 289–291.

Garfield, E. (1963b). *Science Citation Index 1961*, Volume 1. Philadelphia: Institute for Scientific Information, Inc.

Garfield, E. (1965). *Science Citation Index 1964*, Volume 1. Philadelphia: Institute for Scientific Information, Inc.

Garfield, E. (1966). ISI Services in the Design of Small-User Systems. *Journal of Chemical Documentation 6*(3), 164–168.

Garfield, E. (1971). *Science Citation Index Five-Year Cumulation 1965-1969*, Volume 1. Philadelphia: Institute for Scientific Information, Inc.

Garfield, E. (1972). *Science Citation Index 1963*, Volume 1. Philadelphia: Institute for Scientific Information, Inc.

Garfield, E. (1979). *Citation Indexing–Its Theory and Application in Science, Technology, and Humanities*. New York: Wiley.

Garfield, E. (2007). The Evolution of the Science Citation Index. *International Microbiology 10*(1), 65.

Hamermesh, D. S. and P. Schmidt (2003). The Determinants of Econometric Society Fellows Elections. *Econometrica 71*(1), 399–407.

Hengel, E. (2022). Publishing while Female: Are Women Held to Higher Standards? Evidence from Peer Review. *The Economic Journal 132*(648), 2951–2991.

Hilmer, M. J., M. R. Ransom, and C. E. Hilmer (2015). Fame and the Fortune of Academic Economists: How the Market Rewards Influential Research in Economics. *Southern Economic Journal 82*(2), 430–452.

Hirsch, J. E. (2005). An index to quantify an individual's scientific research output. *Proceedings of the National Academy of Sciences 102*(46), 16569–16572.

Hoffman, M., L. B. Kahn, and D. Li (2018). Discretion in Hiring. *The Quarterly Journal of Economics 133*(2), 765–800.

Holmstrom, B. and P. Milgrom (1991). Multitask Principal–Agent Analyses: Incentive Contracts, Asset Ownership, and Job Design. *The Journal of Law, Economics, and Organization 7*(Special Issue), 24–52.

Hsieh, C.-T., E. Hurst, C. I. Jones, and P. J. Klenow (2019). The allocation of talent and u.s. economic growth. *Econometrica 87*(5), 1439–1474.

Iaria, A., C. Schwarz, and F. Waldinger (2018). Frontier Knowledge and Scientific Production: Evidence from the Collapse of International Science. *The Quarterly Journal of Economics 133*(2), 927–991.

Iaria, A., C. Schwarz, and F. Waldinger (2022). Gender Gaps in Academia: Global Evidence Over the Twentieth Century. *Available at SSRN 4150221*.

Jensen, P., J.-B. Rouquier, and Y. Croissant (2009). Testing Bibliometric Indicators by their Prediction of Scientists Promotions. *Scientometrics 78*(3), 467–479.

Jensen, R. (2007, 08). The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector. *The Quarterly Journal of Economics 122*(3), 879–924.

Jin, G. Z., B. Jones, S. F. Lu, and B. Uzzi (2019). The Reverse Matthew Effect: Consequences of Retraction in Scientific Teams. *The Review of Economics and Statistics 101*(3), 492–506.

Jones, B. F. (2009). The Burden of Knowledge and the "Death of the Renaissance Man": Is Innovation Getting Harder? *Review of Economic Studies 76*(1), 283–317.

Jones, C. I. (1995). R & D-Based Models of Economic Growth. *Journal of Political Economy 103*(4), 759–784.

Kantor, S. and A. Whalley (2022). Moonshot: Public R&D and Growth. *Working Paper*.

Katz, A. M. (1971). Hans H. Hecht, MD. *The American Journal of Medicine 51*(6), 829–831.

Koffi, M. (2021). Innovative Ideas and Gender Inequality. *Working Paper*.

Koudijs, P. (2015). Those Who Know Most: Insider Trading in Eighteenth-Century Amsterdam. *Journal of Political Economy 123*(6), 1356–1409.

Lotka, A. J. (1926). The Frequency Distribution of Scientific Productivity. *Journal of the Washington Academy of Sciences 16*(12), 317–323.

Merton, R. K. (1968). The Matthew Effect in Science: The Reward and Communication Systems of Science are Considered. *Science 159*(3810), 55–63.

Muller, E. and R. Peres (2019). The Effect of Social Networks Structure on Innovation Performance: A Review and Directions for Research. *International Journal of Research in Marketing 36*(1), 3–19.

Murphy, K. M., A. Shleifer, and R. W. Vishny (1991). The Allocation of Talent: Implications for Growth. *The Quarterly Journal of Economics 106*(2), 503–530.

Name Census (2023a). Most Common Asian and Pacific Islander Last Names in the United States. `https://namecensus.com/last-names/common-asian-and-pacific-islander-surnames/`.

Name Census (2023b). Most Common Hispanic Last Names in the United States. `https://namecensus.com/last-names/common-hispanic-surnames/`.

Pardo-Guerra, J. P. (2022). *The Quantified Scholar: How Research Evaluations Transformed the British Social Sciences.* New York: Columbia University Press.

Rockoff, J. E., D. O. Staiger, T. J. Kane, and E. S. Taylor (2012). Information and Employee Evaluation: Evidence From a Randomized Intervention in Public Schools. *American Economic Review 102*(7), 3184–3213.

Romer, P. M. (1986). Increasing Returns and Long-Run Growth. *Journal of Political Economy 94*(5), 1002–1037.

Romer, P. M. (1990). Endogenous Technological Change. *Journal of Political Economy 98*(5), 71–102.

Roose, K. D. and C. J. Andersen (1970). *A Rating of Graduate Programs*. Washington: American Council on Education.

Song, J., D. J. Price, F. Guvenen, N. Bloom, and T. Von Wachter (2019). Firming up Inequality. *The Quarterly Journal of Economics 134*(1), 1–50.

Steinwender, C. (2018). Real Effects of Information Frictions: When the States and the Kingdom Became United. *American Economic Review 108*(3), 657–96.

Tadelis, S. and F. Zettelmeyer (2015). Information Disclosure as a Matching Mechanism: Theory and Evidence from a Field Experiment. *American Economic Review 105*(2), 886–905.

Wade, N. (1975). Citation Analysis: A New Tool for Science Administrators. *Science 188*(4187), 429–432.

Waldinger, F. (2010). Quality Matters: the Expulsion of Professors and the Consequences for PhD Student Outcomes in Nazi Germany. *Journal of Political Economy 118*(4), 787–831.

Waldinger, F. (2012). Peer Effects in Science: Evidence from the Dismissal of Scientists in Nazi Germany. *The Review of Economic Studies 79*(2), 838–861.

Weitzman, M. L. (1998). Recombinant Growth. *Quarterly Journal of Economics 113*(2), 331–360.

Wouters, P. (1999a). Beyond the Holy Grail: From Citation Theory to Indicator Theories. *Scientometrics 44*(3), 561–580.

Wouters, P. (1999b). *The Citation Culture*. Amsterdam.

Wouters, P. (2014). The Citation: From Culture to Infrastructure. *Beyond Bibliometrics: Harnessing Multidimensional Indicators of Scholarly Impact 22*, 47–66.

Wouters, P. (2017). Eugene Garfield (1925–2017). *Nature 543*(7646), 492.

Wuchty, S., B. F. Jones, and B. Uzzi (2007). The Increasing Dominance of Teams in Production of Knowledge. *Science 316*(5827), 1036–1039.

Zuckerman, H. and R. K. Merton (1971). Patterns of Evaluation in Science: Institutionalisation, Structure and Functions of the Referee System. *Minerva 9*(1), 66–100.

Appendix

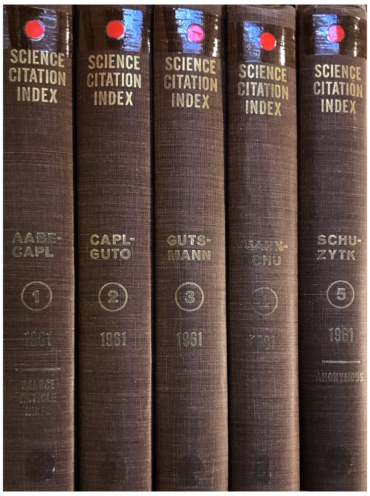
The Appendix presents details on data collection and additional results:

- Appendix A provides further background on the SCI.
- Appendix B provides details on data collection.
- Appendix C reports robustness checks and additional findings on the analysis of assortative matching in Section II.
- Appendix D reports additional findings on the heterogeneity analysis in Section III.
- Appendix E reports additional findings on the analysis of career outcomes in Section IV.

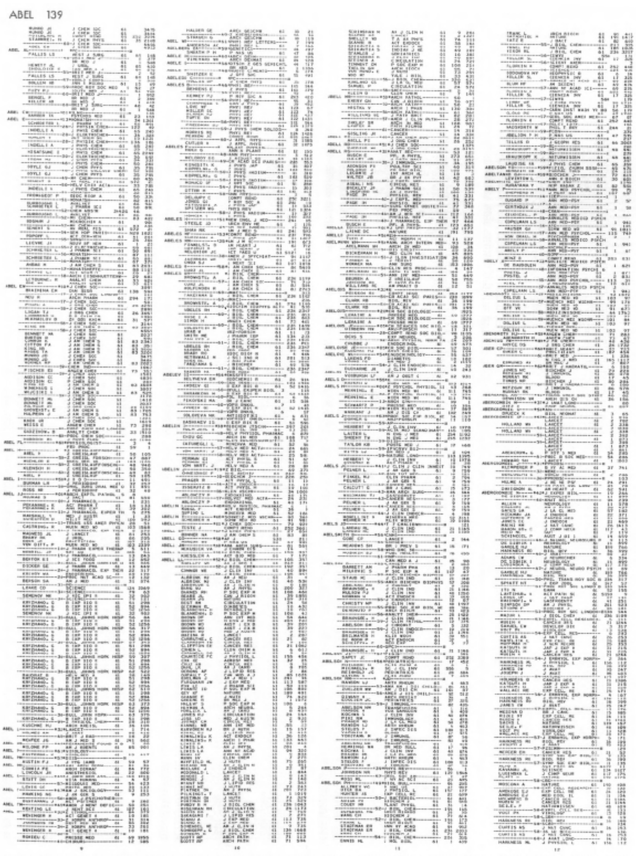
A Background on the SCI

Figure A.1: Entry in Science Citation Index

(a) The 1961 SCI volume



(b) A page in the 1961 SCI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Notes: Panel (a) shows the five books of the 1961 SCI. Panel (b) shows a sample page in the 1961 volume of the SCI.

Figure A.2: 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 I.B).

Figure A.3: 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 University to use the SCI. We thank archivists at Ohio State University Library for sharing this document.

B Further Details on Data

B.1 Data on Scientists

B.1.1 Linking Faculty Rosters with Publication and Citation Data

As described in the main text, we link scientists with their publications and citations using the 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*.

B.1.2 Coding Minority Status

In Section III, we report results on the heterogeneous effect of citation metrics. In particular, in Section III.C, we report differential results for women and for people with Asian, Hispanic, and Jewish names.

We use information in the faculty rosters to tag scientists as members of one of these groups. Gender coding relies on information on gender that can be directly observed in the faculty rosters (e.g., Miss in front of the first name) and the first names of scientists (see Iaria et al. (2022)).

We code Jewish names based on the approach in Benetti et al. (2023). Using their classification of Jewish names results in an overly conservative classification of Jewish scientists. We therefore lower the cut-off for classifying names as distinctively Jewish to 5 (instead of 10). However, results remain very similar when using the cut-off used in Benetti et al. (2023).

The coding of Hispanic 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 all academics who have one of these names as Hispanic.

Similarly, we use data from the U.S. Census to code Asian names. 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%.[34] We then tag all academics who have one of these names as Asian.

B.1.3 Data on NSF Grants

For the analysis in Section IV.B, we match scientists in our faculty rosters with historical records on grants by the National Science Foundation (NSF). We digitize entries on all

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

grants listed in the 1969 Annual Report of the NSF.[35] We then match principal investigators from these grants to the scientists in our data based on first names, last name, and subject.

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 all rankings similar departments are ranked among the top 20 departments.

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

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), a superscript indicates their rank. In the analysis, they are given the same rank.

[35] These data were generously shared by Dan Gross.

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	Harvard	Texas	Cal. Tech.	M.I.T.
4	Princeton	Georgetown College	Johns Hopkins	Cal. Tech.
5	U.C. San Diego	Rockefeller [5]	Rockefeller	Rockefeller
6	Stanford	U.C. San Diego [5]	Wisconsin	Wisconsin
7	Cal. Tech.	U.C. Riverside	Illinois	Stanford
8	Texas	Wisconsin	Michigan	Washington
9	U.C. Berkeley	U.C. Berkeley	Stanford	U.C. San Diego [9]
10	Syracuse	Stanford	Minnesota	Yale [9]
11	Brandeis	U.C. Davis	Indiana [11]	Chicago
12	Yale	Brandeis	Princeton [11]	Illinois
13	Chicago	Princeton	Cornell	Cornell
14	M.I.T.	Notre Dame	Yale	U.C. Davis
15	U.C. Santa Barbara	Whitman College	Purdue [15]	Michigan
16	Notre Dame	Mount Holyoke College	U.C.L.A. [15]	Duke
17	Johns Hopkins	Alma College	Case Western Reserve	U.C.L.A.
18	Whitman College	U.C. Santa Barbara	Washington	Johns Hopkins
19	Washington	Central College Pella [19]	Chicago	Brandeis
20	U.C. Davis	Harvard [19]	Pennsylvania	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), a superscript indicates their rank. In the 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	Harvard	Stanford	U.C. Berkeley	Stanford [3]
4	U.C. Santa Barbara	U.C. Riverside	M.I.T.	U.C. Berkeley [3]
5	U.C.L.A.	U.C. Irvine	Stanford	M.I.T.
6	U.C. Riverside	Southern California	Illinois	Illinois
7	Cal. Tech.	College of Forestry at Syracuse	Columbia [7]	U.C.L.A.
8	Northwestern	Iowa State	Wisconsin [7]	Chicago [8]
9	Southern California	Utah	U.C.L.A.	Columbia [8]
10	College of Forestry at Syracuse	U.C. Davis	Chicago	Cornell [8]
11	Thiel College	Northwestern	Cornell	Wisconsin [8]
12	U.C. Berkeley	Texas	Yale	Yale
13	Iowa State	U.C.L.A.	Princeton	Princeton
14	Rice	Case Western Reserve	Northwestern	Northwestern
15	Illinois	Pennsylvania	Minnesota	Iowa State [15]
16	Utah	Illinois	Iowa State	Purdue [15]
17	Notre Dame	Johns Hopkins	Ohio State [17]	Ohio State [17]
18	U.C. Santa Cruz	Iowa State	Purdue [17]	Texas [17]
19	Columbia	Michigan	Michigan	U.C. San Diego [17]
20	Texas	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), a superscript indicates their rank. In the 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	Harvard [1]
2	Chicago	U.C. Riverside	U.C. Berkeley	U.C. Berkeley [1]
3	Stanford	Harvard	Princeton	Princeton
4	Institute for Advanced Study	Princeton	Chicago	Chicago
5	Harvard	Carnegie-Mellon	M.I.T.	M.I.T.
6	Columbia	Washington	Stanford	Stanford
7	Johns Hopkins	Chicago	Yale	Yale
8	Brandeis	Johns Hopkins	N.Y.U.	N.Y.U.
9	U.C. Berkeley	Rockefeller	Columbia	Wisconsin
10	Virginia Polytechnic Institute	Stanford	Wisconsin	Columbia [10]
11	Rockefeller	Washington Saint Louis	Michigan	Michigan [10]
12	U.C. San Diego	Columbia	Illinois	Cornell [12]
13	Washington	Virginia	Cornell	Illinois [12]
14	Carnegie-Mellon	U.C. San Diego	Cal. Tech.	U.C.L.A.
15	Wisconsin	Wisconsin	Minnesota	Brandeis [15]
16	Yale	Brandeis	U.C.L.A.	Brown [15]
17	Washington Saint Louis	Yale	Washington	Cal. Tech. [15]
18	Case Institute of Technology	Institute for Advanced Study	Brown	Minnesota [18]
19	Brown	Minnesota	Brandeis	Pennsylvania [18]
20	Cornell	Michigan	Johns Hopkins	Washington [18]

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), a superscript indicates their rank. In the 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 [2]
3	Utah	Rutgers	Stanford [2]
4	U.C. San Diego	U.C. San Diego	U.C. San Francisco
5	Minnesota Rochester	Harvard	Yale
6	Rutgers	Amherst College	Columbia
7	Washington	Loretto Heights College	Duke
8	M.I.T.	Medical College of Virginia	Michigan
9	Texas	M.I.T.	Cornell
10	U.C. San Francisco	Washington	Washington Saint Luis
11	Johns Hopkins	U.C.L.A.	Pennsylvania
12	Minnesota	Johns Hopkins	Minnesota
13	U.C.L.A.	Utah	U.C.L.A.
14	Florida	Minnesota	Albert Einstein College
15	New Mexico	Florida [15]	Chicago Pritzker [15]
16	Kansas	Rockefeller [15]	Washington [15]
17	Medical College of Virginia	U.C. San Francisco	Case Western Reserve
18	Washington Saint Louis	Southern California	Rochester
19	Stanford	Mississippi	Colorado
20	Columbia	Wagner College	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), a superscript indicates their rank. In the analysis, they are given the same rank.

Table B.6: Top 20 Departments: Physics

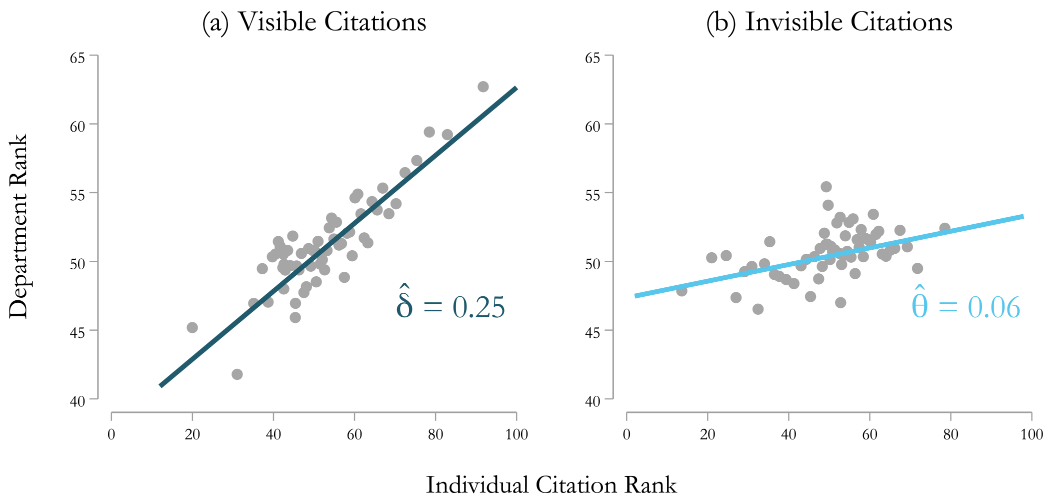
Rank	Citations Ranking	Publications Ranking	Cartter Ranking	Roose-Andersen Ranking
1	U.C. San Diego	U.C. Riverside	U.C. Berkeley	Cal. Tech. [1]
2	U.C. Riverside	U.C. San Diego	Cal. Tech.	Harvard [1]
3	U.C. Berkeley	Lycoming College	Harvard	U.C. Berkeley [1]
4	Chicago	U.C. Santa Barbara	Princeton	Princeton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

C Assortative Matching: Additional Results and Robustness

C.1 Graphical Representation of Specification 1

Figure C.1: Specification 1: Illustration of Results



Notes: The figure illustrates the results from Equation (1), see Table 3, Specification 1. Panel (a) shows a bin-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 slopes are significantly different from each other; the p-value from a t-test of no difference is < 0.001.

C.2 Robustness Checks

In this section, we show that the main results are robust to various changes to the analysis. First, in Appendix C.2.1, we show that results are similar for alternative measures of the department rank. Second, in Appendix C.2.2, we show results are similar for alternative performance measures of individual scientists. Third, in Appendix C.2.3, we show that the results are robust to different ways of assigning percentile ranks to scientists and departments. Last, in Appendix C.2.4, we show that the results hold in different subsamples. To reduce the number of tables, we report all robustness checks using the specification equivalent to column (3) in Table 3, Specification 1. The results are very similar across specifications using alternative control variables, corresponding to columns (1), (2), (4), and (5) in Table 3.

C.2.1 Alternative Department Rankings

First, we consider alternative department rankings. The main results (Table 3) are estimated with department ranks based on the leave-out mean of citations as the dependent variable. 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)).

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, which 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. To avoid unnecessary sample selection for this robustness check, departments that are not listed in these rankings are assigned the percentile rank between 1 and the lowest-ranked department.[36] As these rankings do not cover medical schools, we supplement

[36] This is necessary because these external rankings cover fewer departments than our data. Furthermore, 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). For both the Roose-Andersen ranking and the Cartter ranking, we construct an overall ranking for biology by calculating the average rank of a department in the subfields of biology.

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

	Dependent Variable: Department Rank			
	(1)	(2)	(3)	(4)
Department Ranking Based on:	Leave-Out Mean of Citations	Mean of Citations	Leave-Out Mean of Publications	Mean of Publications
Panel A: Department Rankings From 1969				
Visible Citations	0.280	0.320	0.286	0.318
	(0.035)	(0.030)	(0.034)	(0.028)
Invisible Citations	0.062	0.078	0.047	0.053
	(0.021)	(0.020)	(0.020)	(0.019)
P-value (Visible = Invisible)	< 0.001	< 0.001	< 0.001	< 0.001
Observations	27,315	27,315	27,315	27,315
R^2	0.153	0.207	0.150	0.210
Dependent Variable Mean	50.40	50.20	50.37	50.16
Panel B: Department Rankings From 1956				
Visible Citations	0.169	0.178	0.158	0.175
	(0.038)	(0.039)	(0.037)	(0.039)
Invisible Citations	0.027	0.028	0.006	0.009
	(0.026)	(0.027)	(0.026)	(0.027)
P-value (Visible = Invisible)	< 0.001	< 0.001	< 0.001	< 0.001
Observations	21,269	21,269	21,269	21,269
R^2	0.066	0.066	0.061	0.063
Dependent Variable Mean	50.29	55.59	50.26	56.27
Subject Fixed Effects	Yes	Yes	Yes	Yes
Publications by Year × Subject	Yes	Yes	Yes	Yes

Notes: The table reports the estimates of Equation (1) with alternative department rankings as dependent variables. In Panel A, department rankings are based on the 1969 cross-section of scientists; in Panel B, they are based on the 1956 cross-section. For departments that did not exist in 1956, the 1956 ranking cannot be computed. This results in a smaller sample size in Panel B. In column (1), the dependent variable is the department rank, based on the leave-out mean of citations in the department of scientist i (as in Table 3). In column (2), the department rank is based on the mean of citations in the department. In column (3), the department rank is based on the leave-out mean of publications in the department. In column (4), the department rank is based on the mean of publications in the department. The explanatory variable *Visible Citations* measures scientist i's individual rank in the distribution of visible citations. *Invisible Citations* measures scientist i's individual rank in the distribution of *in*visible citations. We transform ranks into percentiles, where 100 is the best and 1 the worst department/scientist. *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.

these rankings with the first comprehensive ranking of medical schools by Cole and Lipton (1977). We report the results of these tests in Table C.2, column (4). The estimates show that our results are very similar if we use independently compiled reputation-based rankings.

Instead of percentile ranks, we can also use the reputational rankings from Cartter (1966) and Roose and Andersen (1970) to construct indicators for being in a top-ranked department. According to both rankings, we assign each scientist an indicator for whether they worked in a top-five, top-ten, or top-twenty department. In line with our main results, a scientist with a higher visible citation rank was more likely to work in a top department in 1969. For example, a ten-percentile increase in visible citations increased the probability of being affiliated with a top-twenty department by 2.94 percentage points (i.e., a 13.5 percent increase). In contrast, invisible citations had a much smaller effect on the assortativeness of the match to a top-department (Table C.2, columns (1)-(3)).

Table C.2: Robustness Check: External Department Ranking

	Dependent Variable: Indicator			*Dep. Rank*
	(1) Top 5	(2) Top 10	(3) Top 20	(4)
Panel A: Cartter Ranking				
Visible Citations	0.00077	0.00156	0.00294	0.224
	(0.00037)	(0.00039)	(0.00044)	(0.031)
Invisible Citations	0.00023	0.00059	0.00083	0.046
	(0.00018)	(0.00025)	(0.00032)	(0.022)
P-value (Visible = Invisible)	0.282	0.066	0.001	< 0.001
Observations	27,315	27,315	27,315	27,315
R^2	0.050	0.061	0.097	0.104
Dependent Variable Mean	0.04	0.12	0.22	50.15
Panel B: Roose-Andersen Ranking				
Visible Citations	0.00084	0.00166	0.00282	0.249
	(0.00037)	(0.00040)	(0.00043)	(0.032)
Invisible Citations	0.00025	0.00067	0.00096	0.039
	(0.00019)	(0.00025)	(0.00032)	(0.022)
P-value (Visible = Invisible)	0.234	0.061	0.004	< 0.001
Observations	27,315	27,315	27,315	27,315
R^2	0.053	0.065	0.099	0.116
Dependent Variable Mean	0.05	0.12	0.22	50.15
Subject Fixed Effects	Yes	Yes	Yes	Yes
Publications by Year $\times$ Subject	Yes	Yes	Yes	Yes

Notes: The table reports the estimates of Equation (1), where the dependent variable is based on the reputation-based department rankings by Cartter (1966) and Roose and Andersen (1970). Since these rankings do not cover medical schools, for medicine we supplement them with the ranking of medical schools by Cole and Lipton (1977). In columns (1)-(3), the dependent variable is an indicator for whether scientist i was employed at a top-5, top-10, or top-20 department. In column (4), the dependent variable is the rank of scientist i's department. To avoid unnecessary sample selection, we assign departments that are not listed in these rankings to the average rank between 1 and the lowest-ranked department. The explanatory variable *Visible Citations* measures scientist i's individual rank in the distribution of visible citations. *Invisible Citations* measures scientist i's individual rank in the distribution of *in*visible citations. We transform ranks into percentiles, where 100 is the best and 1 the worst department/scientist. *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.

C.2.2 Alternative Transformations of Individual Citation Counts

We also show that results are robust to using alternative ways of measuring the performance of individual scientists.

For the main results, we count citations independently of the number of co-authors on the cited papers. In Table C.3, column (2), we report results of Specification 1, where citations to each paper are divided by the number of authors of the paper. The results are very similar.

Another concern could be that the results are driven by differences in the distributions of visible and invisible citations. Larger measurement error for invisible citations could potentially 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 similar distributions of visible and invisible citations.[37] 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 (3)).

A further concern is that one "superstar" paper may place a scientist at the top of the citation distribution. However, having many moderately cited papers might be a better signal of quality than having very few highly cited papers. To account for both the number of cited papers and for the citations they receive, we use the h-index (e.g., Hirsch, 2005; Ellison, 2013) as an alternative performance metric. A scientist has an h-index of h if h of their papers have at least h citations each. We calculate the h-index of visible and invisible citations for each scientist. We then transform the h-index into the percentile rank for two reasons: first, this makes the coefficient directly comparable to the main results. Second, different scientific subjects have different publication and citation patterns. An h-index of three (i.e., having at least three publications with at least three citations) therefore indicates very different quality percentiles in each subject. For example, in medicine, a subject where scientists publish many papers and receive many citations, an h-index of three indicates poorer performance than in mathematics, a subject where scientists publish relatively few papers and receive a lot fewer citations. When we use percentiles of the visible and invisible h-indices as the explanatory variable, we confirm our main results (Table C.3, column (4)).

We also show that the results are similar if we standardize visible and invisible citations at the subject-level (Table C.3, column (5)). As standardized citations contain large outliers, we show that the results are also robust to winsorizing citation counts at the 99th percentile and then standardizing citation counts (Table C.3, column (6)). Further, the results are also similar if we use the inverse hyperbolic sine transformation of citations (Table C.3, column (7)).

[37] For citations measured in 1956-1965 the summary statistics are as follows. Visible citations: mean 14.3, standard deviation 41.4; invisible citations: mean 17.3, standard deviation 52.1.

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

	Dependent Variable: Department Rank						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable Transformation:	Main Specification	Co-Author Weighted Citations	Only 1956-65 Citations	H-Index	Standard-ized	Winsorized & Std.	Inverse Hyperbolic Sine
Visible Citations	0.280	0.288	0.209	0.267	2.484	4.631	3.294
	(0.035)	(0.034)	(0.029)	(0.033)	(0.693)	(0.543)	(0.567)
Invisible Citations	0.062	0.062	0.119	0.081	0.367	1.461	1.268
	(0.021)	(0.022)	(0.025)	(0.021)	(0.545)	(0.416)	(0.309)
Subject Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Publications by Year × Subject	Yes	Yes	Yes	Yes	Yes	Yes	Yes
P-value (Visible = Invisible)	< 0.001	< 0.001	0.009	< 0.001	0.063	< 0.001	0.002
Observations	27,315	27,315	27,315	27,315	27,315	27,315	27,315
R^2	0.153	0.157	0.139	0.152	0.105	0.116	0.149
Dependent Variable Mean	50.40	50.40	50.40	50.40	50.40	50.40	50.40

Notes: The table reports the estimates of Equation (1) for alternative transformations of visible and invisible citations. The dependent variable is the department rank in 1969, based on the leave-out mean of citations in the department of scientist i. In column (1), the explanatory variable *Visible Citations* measures scientist i's individual rank in the distribution of visible citations. *Invisible Citations* measures scientist i's individual rank in the distribution of *in*visible citations. We transform ranks into percentiles, where 100 is the best and 1 the worst department/scientist. In column (2), citation counts are divided by the number of authors of a paper and then transformed as in column (1). In column (3), citation counts are based only on citations from 1956-1965 (instead of 1956-1969), and then transformed as in column (1). In column (4), the explanatory variables are scientist i's h-index values based on visible and invisible citations, which are then transformed into the percentile rank. In column (5), we standardize citations by subject. In column (6), we standardize citations by subject, but to reduce the weight of outliers, we winsorize citation counts at the 99th percentile before standardizing them. In column (7), we transform citations using the inverse hyperbolic sine. *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.

C.2.3 Scientists and Departments with Zero Citations

When more than one percent of scientists have zero citations, a unique percentile rank cannot be assigned to these scientists. For example, in physics, 30.37% of observations have zero citations. For these scientists, there is no unique percentile in the distribution of citations. In our main analysis, we assign the mid-point between the 1st and the 31st percentile, i.e., a percentile rank of 15.5, to each of these observations. Alternatively, we can assign all of these observations to the 1st percentile (Min.-Point in Table C.4) or to the 31st percentile (Max.-Point). Reassuringly, the exact construction of percentile ranks of scientists with zero citations has no qualitative impact on the findings (Table C.4, columns (2) and (3)). A similar issue can occur for scientists with very low citation counts, e.g., one citation. We treat them accordingly.

Another way of assigning the percentile rank to scientists with zero citations is to spread the specific percentile rank randomly within the group of scientists with zero citations. In the above example of physicists with zero citations, this means that each of these scientists' percentile rank is independently drawn from a uniform distribution from 1 to 31. The results using this alternative transformation are similar to the main results column (4).

Table C.4: Robustness Check: Alternative Percentile Rank Definititions

	Dependent Variable: Department Rank			
	(1)	(2)	(3)	(4)
Variable Transformation:	Mid-Point (Main Spec.)	Min.-Point	Max.-Point	Random For 0 Cit.
Visible Citations	0.280	0.211	0.361	0.238
	(0.035)	(0.022)	(0.059)	(0.029)
Invisible Citations	0.062	0.048	0.107	0.068
	(0.021)	(0.014)	(0.036)	(0.015)
Subject Fixed Effects	Yes	Yes	Yes	Yes
Publications by Year × Subject	Yes	Yes	Yes	Yes
P-value (Visible = Invisible)	< 0.001	< 0.001	< 0.001	< 0.001
Observations	27,315	27,315	27,315	27,315
R^2	0.153	0.155	0.148	0.147
Dependent Variable Mean	50.40	50.03	50.76	50.40

Notes: The table reports the estimates of Equation (1) for alternative constructions of the percentile rank transformation. In all columns, the dependent variable is the department rank in 1969, based on the leave-out mean of citations in the department of scientist i. The explanatory variable *Visible Citations* measures scientist i's individual rank in the distribution of visible citations. *Invisible Citations* measures scientist i's individual rank in the distribution of *in*visible citations. We transform ranks into percentiles, where 100 is the best and 1 the worst department/scientist. The columns differ in how percentile ranks are assigned to brackets that comprise multiple percentiles. In column (1), departments and individuals without citations are assigned a percentile according to the midpoint between 1 and the lowest percentile with positive citations. In column (2), departments and individuals without citations are assigned to the first percentile. In column (3), departments and individuals without citations are assigned to the lowest percentile with positive citations. In column (4), individuals without citations are randomly assigned to a percentile rank within the bracket of zero citations. *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.

C.2.4 Alternative Sample Restrictions

We also 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 (Table C.5, 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.5, column (3)).

Table C.5: Robustness Check: Alternative Sample Restrictions

	Dep. Var.: Department Rank		
	(1)	(2)	(3)
Sample Restriction:	Full Sample	Num. of Cit. > 0	Size of Dept. > 10
Visible Citations	0.280	0.314	0.212
	(0.035)	(0.039)	(0.035)
Invisible Citations	0.062	0.085	0.060
	(0.021)	(0.020)	(0.021)
Subject Fixed Effects	Yes	Yes	Yes
Publications by Year $\times$ Subject	Yes	Yes	Yes
P-value (Visible = Invisible)	< 0.001	< 0.001	< 0.001
Observations	27,315	17,066	22,753
R^2	0.153	0.136	0.135
Dependent Variable Mean	50.40	56.56	54.97

Notes: The table reports the estimates of Equation (1) for alternative subsamples. The dependent variable is the department rank in 1969, based on the leave-out mean of citations in the department of scientist i. The explanatory variable *Visible Citations* measures scientist i's individual rank in the distribution of visible citations. *Invisible Citations* measures scientist i's individual rank in the distribution of *in*visible citations. We transform ranks into percentiles, where 100 is the best and 1 the worst department/scientist. *Publications by Year* separately measure the number of scientist i's publications in each year between 1956 and 1969. In column (1), we use the full sample, i.e., it is equivalent to column (3) in of Table 3, Specification 1. Column (2) reports results 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 ten scientists. Standard errors are clustered at the department level.

C.3 Ruling out Alternative Explanations

In this section, we show that neither differences in the quality of citing journals nor differential timing of citations biases our findings (Tables C.6 and C.7). Figure C.2 illustrates the variation used in these tests.

Figure C.2: Illustration of Variation Used in Additional Tests

(a) Specification 1

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

(b) Alternative Explanation 1

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

(c) Alternative Explanation 2

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

(d) Specification 2

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

Notes: The four panels illustrate the sets of citations used for testing the alternative explanations in Appendix C.3 and for Specification 2 in Section II.C. As in Table 2, these tables illustrate citations for a hypothetical scientist. Panel (a) illustrates the variation used in Specification 1, 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 indexed by the SCI. Numbers in light blue cells indicate citations that were invisible, but are observable today. Panel (b) illustrates the variation used in testing Alternative Explanation 1, i.e., where citations are counted from a consistent set of journals (see Table C.6). We disregard citations in journals that were not indexed by the first SCI in 1961 (here: journals B and C), and focus only on citations in journals that were indexed 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 testing Alternative Explanation 2, i.e., where citation are counted in years in which the SCI was published (see Table C.7). 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 indexed by the SCI. Panel (d) illustrates the variation used in Specification 2, equivalent to Table 4 in the main paper.

Table C.6: Alternative Explanation 1: Citations From Consistent Set of Journals

	Dependent Variable: Department Rank				
	(1)	(2)	(3)	(4)	(5)
Visible Citations	0.289	0.299	0.260	0.228	0.219
	(0.034)	(0.030)	(0.033)	(0.033)	(0.034)
Invisible Citations	0.109	0.075	0.067	0.069	0.066
	(0.022)	(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 (Visible = Invisible)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Observations	27,315	27,315	27,315	27,315	27,315
R^2	0.129	0.131	0.147	0.228	0.257
Dependent Variable Mean	50.40	50.40	50.40	50.40	50.40

Notes: The table reports the estimates of Equation (1), where individual citation counts are based only on the restricted set of citing journals that were indexed in the 1961 edition of the SCI. The dependent variable is the department rank in 1969, based on the leave-out mean of citations in the department of scientist i. The explanatory variable *Visible Citations* measures scientist i's individual rank in the distribution of visible citations in the restricted set of citing journals. *Invisible Citations* measures scientist i's individual rank in the distribution of *in*visible citations in the restricted set of citing journals. We transform ranks into percentiles, where 100 is the best and 1 the worst department/scientist. *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*). Standard errors are clustered at the department level.

Table C.7: Alternative Explanation 2: Citations Only From Years With SCI

	Dependent Variable: Department Rank				
	(1)	(2)	(3)	(4)	(5)
Visible Citations	0.342	0.347	0.302	0.275	0.263
	(0.039)	(0.035)	(0.040)	(0.040)	(0.041)
Invisible Citations	0.066	0.047	0.046	0.033	0.037
	(0.017)	(0.014)	(0.014)	(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 (Visible = Invisible)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Observations	27,315	27,315	27,315	27,315	27,315
R^2	0.137	0.140	0.153	0.232	0.260
Dependent Variable Mean	50.40	50.40	50.40	50.40	50.40

Notes: The table reports the estimates of Equation (1), where individual citation counts are based only the restricted set of citations from years when the SCI was available, i.e., 1961 and 1964-1969. The dependent variable is the department rank in 1969, based on the leave-out mean of citations in the department of scientist i. The explanatory variable *Visible Citations* measures scientist i's individual rank in the distribution of visible citations in the restricted citation years. *Invisible Citations* measures scientist i's individual rank in the distribution of *in*visible citations in the restricted citation years. We transform ranks into percentiles, where 100 is the best and 1 the worst department/scientist. *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*). Standard errors are clustered at the department level.

While the test for Alternative Explanation 2 in Table C.7 considers only citations in years in which the SCI was published, one might still be concerned that even in this subset of citations, visible citations, on average, come from later years. If later citations are more important for career outcomes in 1969, this might still bias the results.

We address this concern by repeating the robustness test for smaller time windows within the years covered by the SCI. In Table C.8, we present the results for five different regressions in which we only count visible and invisible citations within five three-year windows (1961 and 1964-1965, 1964-1966, 1965-1968, 1966-1968, and 1967-1969). This enables us to abstract from the timing of citations and consider almost exclusively across-journal variation in visibility. We show that the difference between visible and invisible citations remains unchanged. Furthermore, the actual time window of measuring visible and invisible citations only has a small impact on the estimates. This corroborates the finding in Table C.7, that the timing of visible and invisible citations does not drive our results.

Table C.8: Alternative Explanation 2: Restricted Time Windows

	Dependent Variable: Department Rank				
	(1)	(2)	(3)	(4)	(5)
Citation Years:	1961, 1964-65	1964-66	1965-67	1966-68	1967-69
Visible Citations	0.278	0.293	0.302	0.305	0.302
	(0.038)	(0.039)	(0.039)	(0.039)	(0.039)
Invisible Citations	0.050	0.040	0.054	0.072	0.085
	(0.013)	(0.013)	(0.015)	(0.016)	(0.016)
Subject Fixed Effects	Yes	Yes	Yes	Yes	Yes
Publications by Year × Subject	Yes	Yes	Yes	Yes	Yes
P-value (Visible = Invisible)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Observations	27,315	27,315	27,315	27,315	27,315
R^2	0.141	0.145	0.147	0.149	0.150
Dependent Variable Mean	50.40	50.40	50.40	50.40	50.40

Notes: The table reports the estimates of Equation (1), where individual citation counts are based on restricted sets of citations from years when the SCI was available. The dependent variable is the department rank in 1969, based on the leave-out mean of citations in the department of scientist i. The explanatory variable *Visible Citations* measures scientist i's individual rank in the distribution of visible citations in the restricted citation years. *Invisible Citations* measures scientist i's individual rank in the distribution of *in*visible citations in the restricted citation years. We transform ranks into percentiles, where 100 is the best and 1 the worst department/scientist. In column (1), visible and invisible citation counts are based on the years 1961 and 1964-65; in column (2) 1964-66; in column (3) 1965-67; in column (4) 1966-68; and in column (5) 1967-69. *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.

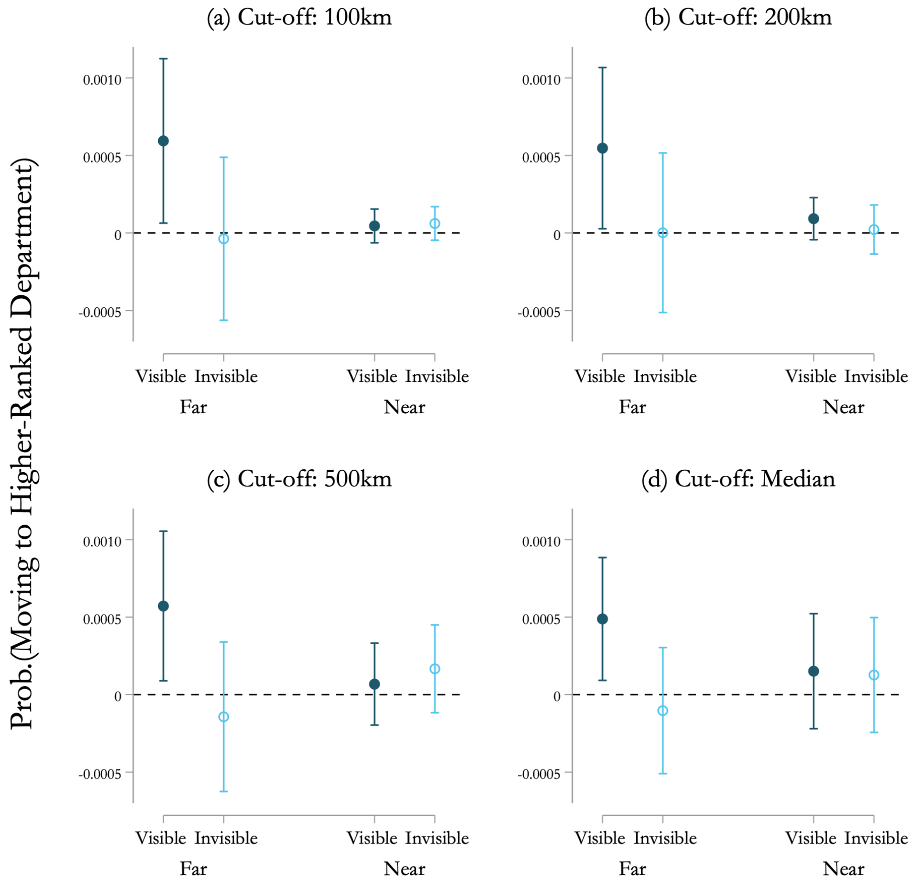
C.4 Additional Findings

Table C.9: Moving to Higher-Ranked Department by Geographic Distance

Dependent Variable: Moving to Higher-Ranked Department by Geographic Distance					
	(1)	(2)	(3)	(4)	(5)
Panel A: New Department Far					
Visible Citations	0.0007	0.0006	0.0006	0.0008	0.0006
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Invisible Citations	-0.0001	0.0000	-0.0000	-0.0004	-0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
P-value (Visible = Invisible)	0.097	0.227	0.220	0.070	0.154
Observations	6,478	6,478	6,478	6,478	6,478
R^2	0.013	0.017	0.036	0.332	0.398
Dependent Variable Mean	0.042	0.042	0.042	0.042	0.042
Panel B: New Department Near					
Visible Citations	0.0000	0.0000	0.0000	0.0000	0.0001
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Invisible Citations	0.0000	0.0000	0.0001	0.0000	-0.0000
	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
P-value (Visible = Invisible)	0.952	0.797	0.873	0.976	0.742
Observations	6,478	6,478	6,478	6,478	6,478
R^2	0.001	0.003	0.021	0.321	0.442
Dependent Variable Mean	0.004	0.004	0.004	0.004	0.004
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 from variants of Equation (3) with different dependent variables: in Panel A, an indicator for moving to a higher-ranked department that was far from scientist i's department; in Panel B, an indicator for moving to a higher-ranked department that was close to scientist i's department. The cut-off between near and far departments is 100km. These regressions use the sample of scientists observed in 1956 and 1969. The explanatory variable *Visible Citations* measures scientist i's individual rank in the distribution of visible citations. *Invisible Citations* measures scientist i's individual rank in the distribution of *in*visible citations. We transform ranks into percentiles, where 100 is the best and 1 the worst scientist. *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*). Standard errors are clustered at the department level.

Figure C.3: Moving to Higher-Ranked Departments by Geographic Distance - Alternative Cutoffs



Notes: The figure plots coefficients and 95 percent confidence intervals from variants of Equation (3). Each panel reports results from two regressions with alternative dependent variables: (i) an indicator for moving to a higher-ranked department that was far from scientist i's department; (ii) an indicator for moving to a higher-ranked department that was close to scientist i's department. In panel (a) the cut-off between near and far departments is 100km; in panel (b) 200km; in panel (c) 300km; and in panel (d) 837km, which is the median distance of moves.

Table C.10: Moving to Higher-Ranked Department by Citation Distance

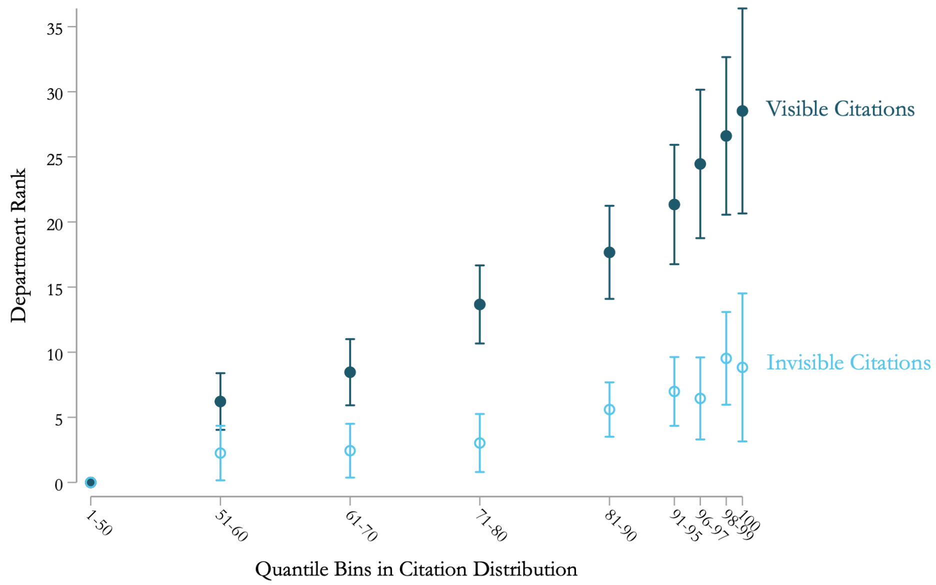
	Dependent Variable: Moving to Higher-Ranked Department by Citation Distance				
	(1)	(2)	(3)	(4)	(5)
Panel A: Not Cited In New Department Before SCI					
Visible Citations	0.0007	0.0007	0.0006	0.0008	0.0007
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Invisible Citations	-0.0004	-0.0002	-0.0002	-0.0005	-0.0005
	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
P-value (Visible = Invisible)	0.027	0.082	0.110	0.034	0.053
Observations	6,478	6,478	6,478	6,478	6,478
R^2	0.008	0.012	0.026	0.294	0.360
Dependent Variable Mean	0.035	0.035	0.035	0.035	0.035
Panel B: Cited In New Department Before SCI					
Visible Citations	0.0001	-0.0000	0.0000	0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Invisible Citations	0.0004	0.0003	0.0002	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
P-value (Visible = Invisible)	0.019	0.051	0.209	0.333	0.208
Observations	6,478	6,478	6,478	6,478	6,478
R^2	0.020	0.030	0.060	0.439	0.533
Dependent Variable Mean	0.011	0.011	0.011	0.011	0.011
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 from variants of Equation (3) with different dependent variables: in Panel A, an indicator for moving to a higher-ranked department where scientist i's papers were not cited before 1963; in Panel B, an indicator for moving to a higher-ranked department where scientist i's papers were cited before 1963. These regressions use the sample of scientists observed in 1956 and 1969. The explanatory variable *Visible Citations* measures scientist i's individual rank in the distribution of visible citations. *Invisible Citations* measures scientist i's individual rank in the distribution of *in*visible citations. We transform ranks into percentiles, where 100 is the best and 1 the worst scientist. *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*). Standard errors are clustered at the department level.

D Additional Findings: Heterogeneity Analysis

D.1 Heterogeneous Effect in Non-Parametric Analysis

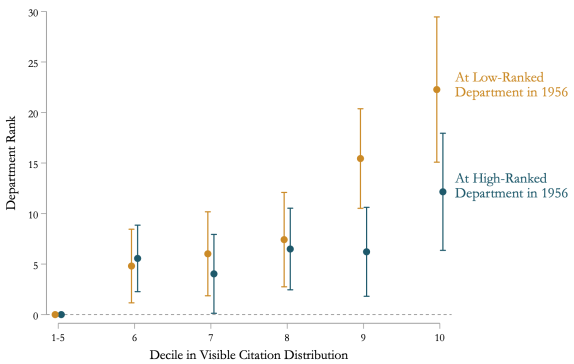
Figure D.1: Heterogeneous Effects by Percentile Rank



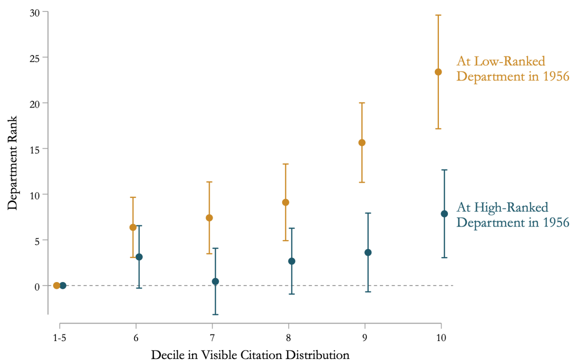
Notes: The figure plots coefficients $\hat{\delta}_q$ (dark blue) and $\hat{\theta}_q$ (light blue) and 95 percent confidence intervals from a variant of Equation (5). It differs from Figure 9 in that it splits up the 10th decile into smaller percentile bins.

Figure D.2: Heterogeneous Effects for Peripheral Scientists

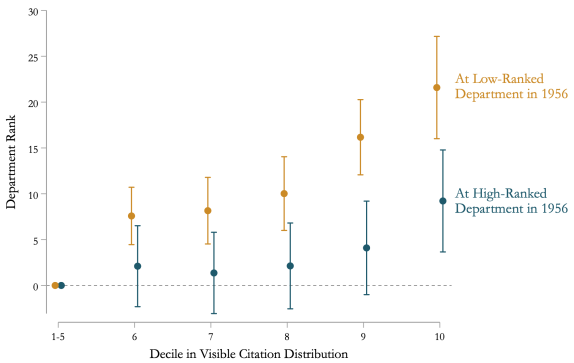
(a) Cutoff: 60th percentile



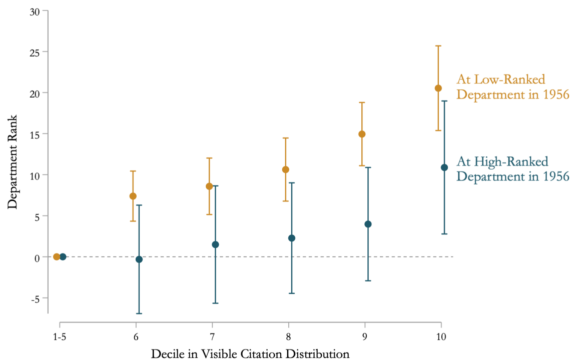
(b) Cutoff: 70th percentile



(c) Cutoff: 80th percentile



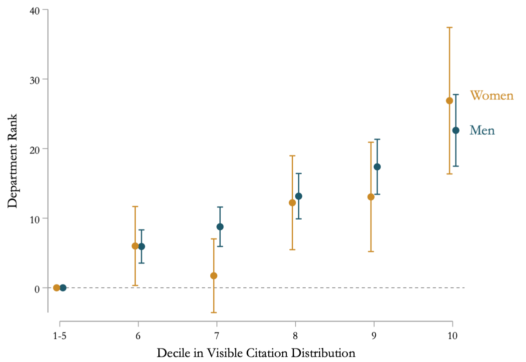
(d) Cutoff: 90th percentile



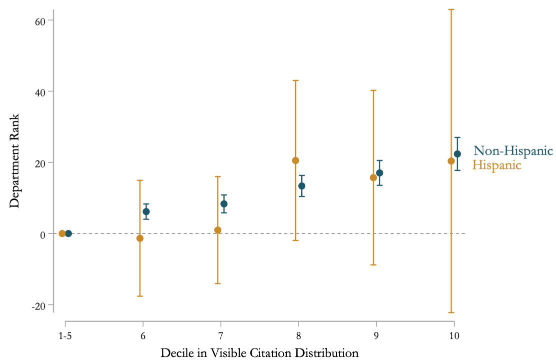
Notes: The figure plots coefficients $\hat{\delta}_q^H$ (orange) and $\hat{\delta}_q^L$ (blue) and 95 percent confidence intervals from Equation (6) for alternative cutoffs of high and low-ranked departments. In panel (a) we define low-ranked departments as those below the 60th percentile of the department 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.

Figure D.3: Heterogenous Effects for Minority Scientists

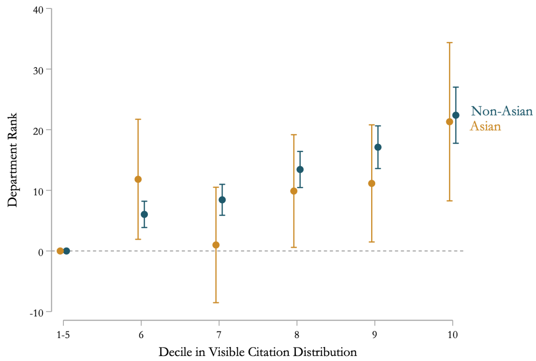
(a) Female Academics



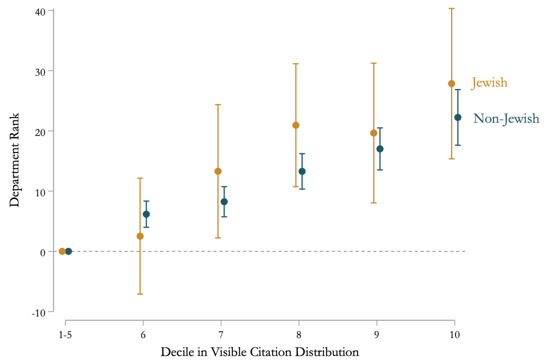
(b) Academics with Hispanic Names



(c) Academics with Asian Names

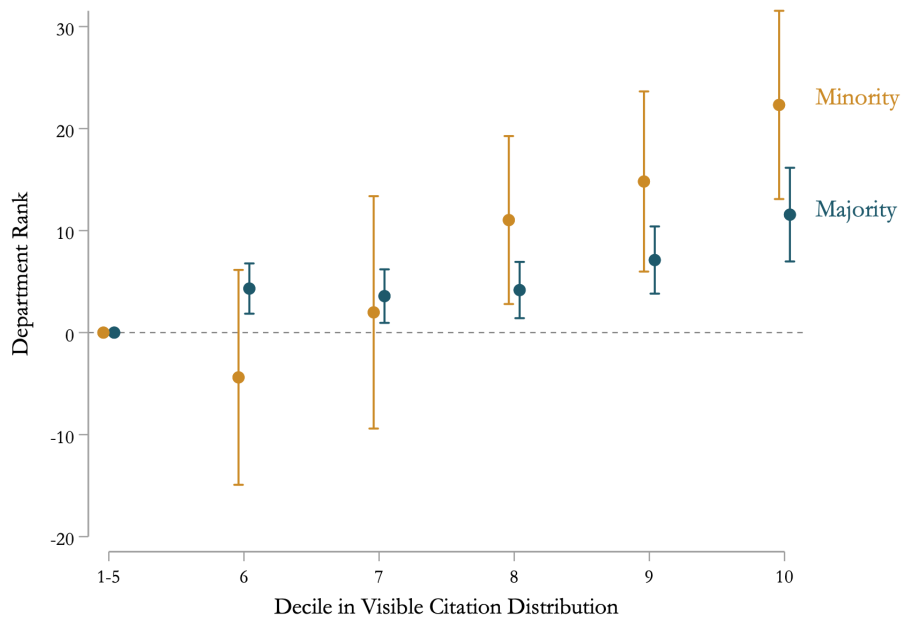


(d) Academics with Jewish Names



Notes: The figure plots coefficients $\hat{\delta}_q^M$ (blue) and $\hat{\delta}_q^m$ (orange) and 95 percent confidence intervals from Equation (7). Panel (a) plots separate sets of coefficients for women (orange) and men (blue). Panel (b) plots separate sets of coefficients for Hispanics (orange) and Non-Hispanics (blue). Panel (c) plots separate sets of coefficients for Asians (orange) and Non-Asians (blue). Panel (d) plots separate sets of coefficients for Jewish (orange) and Non-Jewish scientists (blue).

Figure D.4: Heterogenous Effects for Minority and Majority Scientists (Controlling For Department Rank in 1956)



Notes: The figure plots coefficients $\hat{\delta}_q^M$ (blue) and $\hat{\delta}_q^m$ (orange) and 95 percent confidence intervals from a variant of Equation (7), while controlling for the department rank of scientist in 1956. As a result, the sample is restricted to scientists who appear in both 1956 and 1969. The p-value for the test that the coefficients for the tenth decile are the same among minority and majority scientists is 0.034.

D.2 Heterogeneous Effect on Assortative Matching

In Sections III.B and III.C, 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 (6) and (7). Below, we report additional results on the heterogeneous effect of citation metrics on assortative matching based on a variant of the main specification (Equation (1)):

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

$Indicator_i$ takes value 1 if scientist i is a 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)
Definition of Low-Ranked Department:	Below 60	Below 70	Below 75	Below 80	Below 90
Visible Citations	0.168	0.112	0.088	0.119	0.176
	(0.043)	(0.038)	(0.040)	(0.047)	(0.070)
Invisible Citations	-0.001	-0.011	-0.008	-0.025	-0.074
	(0.035)	(0.035)	(0.036)	(0.042)	(0.058)
Visible Citations × Indicator	0.075	0.138	0.169	0.151	0.100
	(0.059)	(0.050)	(0.052)	(0.057)	(0.076)
Invisible Citations × Indicator	0.071	0.097	0.099	0.121	0.191
	(0.054)	(0.052)	(0.051)	(0.053)	(0.064)
Indicator	-36.700	-41.744	-43.410	-42.901	-40.917
	(3.488)	(3.273)	(3.368)	(3.688)	(5.275)
Subject Fixed Effects	Yes	Yes	Yes	Yes	Yes
Publications by Year × Subject	Yes	Yes	Yes	Yes	Yes
Observations	6,374	6,374	6,374	6,374	6,374
R^2	0.394	0.367	0.351	0.319	0.240
Dependent Variable Mean	59.47	59.47	59.47	59.47	59.47

Notes: The table reports the estimates of Equation (D.1), where the indicator captures whether scientist i was working at a low-ranked department in 1956. The dependent variable is the department rank in 1969, based on the leave-out mean of citations in the department of scientist i. The explanatory variable *Visible Citations* measures scientist i's individual rank in the distribution of visible citations. *Invisible Citations* measures scientist i's individual rank in the distribution of *in*visible citations. We transform ranks into percentiles, where 100 is the best and 1 the worst department/scientist. *Indicator* is equal to one if scientist i worked at a low-ranked department in 1956. Thus, the sample 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 estimates using different definitions of low-ranked department: 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.

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

	Dependent Variable: Department Rank					
	(1)	(2)	(3)	(4)	(5)	(6)
Group Indicator:	Main	Female	Asian	Hispanic	Jewish	Any Minority
Visible Citations	0.280	0.285	0.281	0.280	0.279	0.270
	(0.035)	(0.040)	(0.035)	(0.035)	(0.035)	(0.033)
Invisible Citations	0.062	0.049	0.063	0.062	0.063	0.064
	(0.021)	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)
Visible Citations × Indicator		-0.053	-0.050	0.068	0.049	0.020
		(0.050)	(0.076)	(0.181)	(0.088)	(0.044)
Invisible Citations × Indicator		-0.050	-0.043	0.035	-0.050	-0.039
		(0.055)	(0.084)	(0.179)	(0.087)	(0.043)
Indicator		-2.871	2.452	-5.042	5.754	-5.772
		(2.472)	(3.262)	(5.556)	(3.352)	(2.632)
Subject Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Publications by Year × Subject	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27,315	24,529	27,315	27,315	27,315	27,315
R^2	0.153	0.162	0.153	0.153	0.154	0.159
Dependent Variable Mean	50.40	48.08	50.40	50.40	50.40	50.40

Notes: The table reports the estimates of Equation (D.1), where the indicator captures whether scientist i is part of a minority group. The dependent variable is the department rank in 1969, based on the leave-out mean of citations in the department of scientist i. The explanatory variable *Visible Citations* measures scientist i's individual rank in the distribution of visible citations. *Invisible Citations* measures scientist i's individual rank in the distribution of *in*visible citations. We transform ranks into percentiles, where 100 is the best and 1 the worst department/scientist. *Indicator* is equal to one if scientist i is part of a minority group. Column (1) reports estimates of the main specification for reference (see column (3) in Table 3, Specification 1). Columns (2)-(5) report estimates from regressions where the indicator captures if scientist i is part of a minority group: female in column (2), Asian in column (3), Hispanic in column (4), and Jewish in column (5). Column (6) reports the estimates from a regression where the indicator equals one if scientist i is part of any one of these subgroups. *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.

E Additional Findings: Career Outcomes

Table E.1: Receiving an NSF Grant

	Dependent Variable: Receiving NSF Grant				
	(1)	(2)	(3)	(4)	(5)
Specification 1: Visible vs. Invisible Citations					
Visible Citations	0.0013	0.0013	0.0009	0.0008	0.0007
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Invisible Citations	-0.0001	-0.0001	-0.0002	-0.0001	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
P-value (Visible = Invisible)	< 0.001	< 0.001	< 0.001	< 0.001	0.001
R^2	0.066	0.067	0.107	0.221	0.268
Specification 2: Visible vs. Pseudo-Visible vs. Invisible Citations					
Visible Citations	0.0014	0.0014	0.0009	0.0008	0.0007
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Pseudo-Visible Citations	-0.0005	-0.0005	-0.0005	-0.0003	-0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Invisible Citations (SCI years)	0.0001	0.0001	0.0001	0.0002	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Invisible Citations (non-SCI years)	0.0003	0.0003	0.0003	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
P-value (Visible = Pseudo-Visible)	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
P-value (Visible = Invisible (SCI))	< 0.001	< 0.001	< 0.001	0.001	0.001
P-value (Visible = Invisible (non-SCI))	< 0.001	< 0.001	< 0.001	0.001	0.003
P-value (Pseudo-Vis. = Invis. (SCI) = Invis. (non-SCI))	< 0.001	< 0.001	< 0.001	0.021	0.067
R^2	0.067	0.068	0.108	0.222	0.268
Subject Fixed Effects	Yes	Yes	Yes	Yes	Yes
Publications by Year		Yes			
Publications by Year × Subject			Yes	Yes	Yes
Publications by Journal				Yes	
Publications by Journal × Subject					Yes
Observations	27,315	27,315	27,315	27,315	27,315
Dependent Variable Mean	0.039	0.039	0.039	0.039	0.039

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