

Men set their own cites high: Gender and self-citation across fields and over time

Authors:

Molly M. King - Department of Sociology, Stanford University, Stanford, CA
Carl T. Bergstrom - Department of Biology, University of Washington, Seattle, WA
Shelley J. Correll - Department of Sociology, Stanford University, Stanford, CA
Jennifer Jacquet - Department of Environmental Studies, New York University, New York, NY
Jevin D. West – Information School, University of Washington, Seattle, WA

Acknowledgments and funding:

This work was supported in part by a NSF Graduate Research Fellowship (grant DGE-1147470) to MMK, a John Templeton Foundation Metaknowledge Network grant to JDW and CTB, and a generous gift from JSTOR. The authors thank Erin Leahey, Erin Cech, Flo Débarre and David Miller for feedback on earlier drafts of the paper. The authors also thank the Mathematica Stack Exchange community for assistance in creating Figure 3, and Armand Rundquist, Pooja Loftus, and Jason Hirshman for technical and statistical assistance.

Key words:

Authorship
Citations
Gender
Careers
Networks
Sociology of science

Corresponding author:

Molly M. King
Stanford University
Department of Sociology
450 Serra Mall
Building 120, Room 160
Stanford, CA 94305-2047
Email: kingmo@stanford.edu

Code and figures available:

Open Science Framework Repository - osf.io/de853

Currently under review

ABSTRACT

How common is self-citation in scholarly publication and does the practice vary by gender? Using novel methods and a dataset of 1.5 million research papers in the scholarly database JSTOR published between 1779-2011, we find that nearly 10% of references are self-citations by a paper's authors. We further find that over the years between 1779-2011, men cite their own papers 56% more than women do. In the last two decades of our data, men self-cite 70% more than women. Women are also more than ten percentage points more likely than men to not cite their own previous work at all. Despite increased representation of women in academia, this gender gap in self-citation rates has remained stable over the last 50 years. We break down self-citation patterns by academic field and number of authors, and comment on potential mechanisms behind these observations. These findings have important implications for scholarly visibility and likely consequences for academic careers.

INTRODUCTION

Women remain underrepresented among tenured faculty in US universities, even though they have received more bachelor's degrees for over 30 years and the number of women in postbaccalaureate programs has exceeded men nearly that long (NCES 2013). In 2014, women earned 46% of all research doctorates, including 42% of science and engineering doctorate degrees (NSF 2015a). Even in a perfectly egalitarian hiring and promotion system, the lag in obtaining tenure means it will take time to see parity at tenured ranks. In the social sciences, where women have earned PhDs at a higher rate than men for two decades (NSF 2015a, 2015b), we still see women underrepresented in faculty positions (NSF 2015c). Further, women are underrepresented in senior ranks of faculty, even after controlling for factors such as experience (reviewed in Bentley and Adamson 2004). Among doctoral scientists and engineers at four year institutions in 2013, 28% of tenured faculty were women, compared to 42% on the tenure track and 46% who were not in tenure track positions (NSF 2013). Women are also underrepresented as faculty in the most elite universities (NSF 2015c; Weisshaar n.d.).

Controlling for numbers of papers authored as well as other institutional factors, women assistant professors are still less likely their men counterparts to receive tenure (Weisshaar n.d.). At institutions offering tenure in 2011-2012, 54% of men but only 41% of women full-time instructional faculty had tenure (NCES 2013). These status differences translate to real-world economic outcomes. Most studies show that women faculty earn less than men faculty (reviewed in Bentley and Adamson 2004). In the 2012-2013 academic year, men faculty earned about 22% more than women faculty at degree-granting two- and four-year institutions (average salary: \$84,000 versus \$69,100) (NCES

2013).

Research productivity is a key factor in promotion decisions. Academia is unusual among professions in that productivity is relatively easily measured either by counting the number of publications a scholar has produced or by assessing the quality of her or his publications. To assess quality, researchers and promotion committees often consider “journal impact factors,” which measure the reputation of the journals in which an author’s papers appear, and citation counts, which measure the extent to which the paper is cited. With these purportedly precise measures of productivity, we would expect that non-merit factors like gender would have a smaller effect on promotion than they would in professions with less clear measures of productivity. However, a study of three academic disciplines – computer science, sociology, and English – finds that men were significantly more likely to earn tenure than women junior faculty, controlling for a diverse set of research productivity measures (Weisshaar n.d.).

But what if quantitative productivity measures themselves contain non-merit factors? In this paper, we analyze 1.5 million academic papers from the JSTOR corpus to assess whether men academics cite their own papers more frequently than do women scholars. If men are more likely to cite their own work, their papers will appear to be higher quality partly because of men’s own efforts at self-promoting them.¹

¹ Self-promotion need not be a conscious strategy. Indeed, because self-promoting

We further look at the gender patterns of self-citations over time. Two contradictory hypotheses are in tension here. Since the relative number of women in academia has grown over time (Hill, Corbett, and St. Rose 2010; NCES 2013; NSF 2015c), we expected gender gaps in self-citation to decrease. With more time in the profession, men have had more time to write papers and more time to cite the papers they have written. This implies that as women have been in the profession longer, the gender gap in self-citation should decrease. On the other hand, as academic jobs have become more competitive and the measures quantifying citations have become more important, scholars may feel more pressure to cite their own work as a way of boosting their own productivity ratings. If this pressure has caused men to be ever more likely to self-promote their work than women (Moss-Racusin, Phelan, and Rudman 2010), we might expect that gender gaps in self-citations would have increased over time.

As described below, we find that self-citations represent 10% of all paper citations in the JSTOR corpus. Given the importance of publications and citations to an academic's career success, it is important to understand whether there is a gendered pattern to self-citations, whether that pattern has changed over time, and if the pattern

behaviors are discouraged for women but not for men, self-promoting behavior may be more common for men than women (Rudman et al. 2012). Even so, greater self-citation does increase citation count, thereby increasing the perceived quality of a paper.

varies by academic field.

In the next section, we review the literature on gender and academic research productivity and, more specifically, the few, smaller studies that have examined self-citation patterns. We then describe our data, which covers 1.5 million papers dating back to 1779. These are the largest and most comprehensive data ever used to examine gender and self-citations. We use a hierarchical classification algorithm to reveal the nested structure of fields and subfields. We assign gender to 2.8 million authors based on first name, then calculate the rates of self-citation by gender within years and within fields. We also employ bootstrap methods to develop confidence intervals for our descriptive results. We find a substantial gender gap in self-citations favoring men in most fields.

Gender and Academic Research Productivity

Who publishes more papers?

Research reveals common patterns of gender differences in publication. Several studies find women faculty tend to publish fewer papers than men faculty (reviewed in Bentley and Adamson 2004). Gender differences in self-reported productivity differ by career stage and field (Ceci et al. 2014: Figure 14); findings also vary based on the measure used and controls employed (Ceci et al. 2014: Table 2). The broadest evidence we have of gender differences in productivity comes from a global study of the proportions of authorships in papers in the Web of Science database. Men academics dominated scientific production both globally and in the U.S. as recently as 2008-2012 (Larivière et al. 2013). However, this study measured overall gender differences in academic contributions, not individual differences (not controlling for overall proportions

of men and women academics). In a study of assistant professors in sociology, computer science, and English, gender differences in productivity varied by field and type of publication: for example, men published significantly more top journal articles than women in the fields of sociology and English, but there was no difference in computer science; there was also no gender difference in the number of books or book chapters published in any field (Weisshaar n.d.).

Other findings emphasize that any gender differences in productivity are products of other social or institutional forces, rather than of differences in talent or intelligence. Gender difference in numbers of papers published may be partially explained by gendered tendencies to collaborate, homophilous gender sorting into coauthor teams, and gender differences in the prestige of universities where men and women are employed (reviewed in Bentley and Adamson 2004). Several studies find that women have a greater propensity to collaborate (Abramo, D'Angelo, and Murgia 2013) and to have more collaborators (Bozeman and Gaughan 2011), while others find no gender differences in collaboration patterns (Hunter and Leahey 2008; Long 1992).

Faculty are more likely to coauthor with others of the same gender, at least in economics (Ferber and Teiman 1980; McDowell and Smith 1992). If the finding that scholars are more likely to collaborate with scholars of the same gender extends to other fields, this would put faculty women at a numerical disadvantage. Since there are fewer women in most fields, homophily in collaborations would result in women having fewer potential collaborators with whom to collaborate. Strong collaborative partnerships play a very important part in above-average productivity and increased citation counts (Petersen 2015). Consistent with this prediction, women in STEM fields, which are male-

dominated, do report less satisfaction than their men colleagues with opportunities to collaborate with senior colleagues (Hill et al. 2010; MIT 1999, 2011).

Institutional resources may also contribute to the gender gap in number of publications. Overall women tend to be tenured in less prestigious jobs with heavier teaching responsibilities (Weisshaar n.d.), thereby reducing the relative amount of time they have to spend writing papers. In one of the strongest existing studies on gender differences in productivity, Xie and Shauman (1998) looked at academics in the biological sciences, engineering, mathematics, physical sciences, and social sciences using cross-sectional data from 1969 to 1993. Women tended to publish less than men, but this difference shrank over the 24 years studied. The authors attribute between 7 and 13 percent of the gender gap in research productivity to each of two institutional factors (institution type and research funding), and this explanation is consistent across 4 different data sources. Field, rank, experience, teaching hours, and research assistance each contribute around 6 percent to the gender disparity in productivity. Individual characteristics (marital status and time to PhD) also have a small explanatory effect (Xie and Shauman 1998). The difference does not appear to be the result of women working fewer hours: in a survey of natural science faculty at 13 leading research universities, men and women reported working the same average hours per week (56.4 for men and 56.3 for women) (Schiebinger and Gilmartin 2010).

Who publishes more important papers? Gender, citations and self-citations

While the quantity of papers authored certainly matters, simple publication count is not the only important metric of research productivity. The reputation of the journal in

which a paper is published (often quantified using journal impact factors), along with the number of citations that a paper receives (i.e., other articles that reference that particular work), are common proxies for a publication's importance and influence. Given the importance of publication metrics in academic hiring, tenure and salary decisions, examining gender differences in citation patterns may shed light on persisting gender discrepancies in faculty hiring and promotion.

Self-citation may have a consequential impact on overall citations by both directly and indirectly increasing an author's citation counts. One study found that each additional self-citation yielded *an additional three citations from other scholars* over a five-year period (Fowler and Aksnes 2007).

Research shows that papers authored by women receive fewer citations than do papers by men, when controlling for tenure status, institution, and journal. Larivière and colleagues (2013) examined the relationships between gender and research output for over 5 million papers from the Web of Science. Women in first or sole author positions receive fewer citations than men in the same positions (Larivière et al. 2013). In a study of articles published in the international relations literature between 1980 and 2006, papers in the same journal, published through the same peer-review process, are cited less often when written by women than when written by men (Maliniak, Powers, and Walter 2013). Relative citation levels per author depend on the point in time in the academic's career, at least among biochemists receiving their PhDs between 1950 and 1967; in the early career years, women's average number of citations per year is lower than men's, but by year 17, citation levels even out. In this same data, however, women have a higher average number of citations per paper: by career year 17, the average biochemist's paper

is cited between 9 and 13 times if she is a woman or between 7 and 9 times if he is a man (Long 1992). In other words, this early cohort of senior women faculty were writing fewer papers, but each was being cited more than male faculty in equivalent positions.

As Rossiter (1993) has documented, women's academic contributions to science have been undervalued historically. She refers to the process by which women's scientific contributions are downplayed or ignored relative to men's as the “Matilda Effect.”² This phrase contrasts with the well-known “Matthew Effect,” which refers to the psychosocial process of cumulative advantage, by which eminent scientists receive credit disproportionately to their contributions (Merton 1968, 1988). There is then a “continuing interplay between the status system, based on honor and esteem, and the class system, ... which locates scientists in differing positions within the opportunity structure of science,” providing eminent scientists with further advantages in the quest to contribute (Merton 1968: 57). Recognition is a primary source of barter and reward in scientific careers, underscoring the importance of understanding citation patterns as part of the Matthew and Matilda Effects.

² Evidence of such gender differences in evaluations of scientific contributions is also perceived in gender-differentiated ways. Results from three different experiments, using samples of both public and scientific communities, showed that men evaluate evidence of gender bias in science as less meritorious than do women (Handley et al. 2015).

To date, studies of self-citation have been few in number and confined to a limited number of disciplines and a relatively small number of papers. One reason there have been so few self-citation studies is that publishers do not tend to provide free access to full citation databases. Another reason is the difficulty of disambiguating author names.

To our knowledge, only two studies that looked at self-citation included any analysis of gender. Research analyzing twelve journals in the field of international relations from 1986-2000 showed that men cite their own papers more than one and a half times as often as women (Maliniak et al. 2013). A study of papers in five archaeology publications also found that men tend to cite themselves slightly more often than women. However, this trend was not statistically significant, leading the author to conclude there was no gender difference in self-citation (Hutson 2006). The lack of significance could have been due to the small sample size.

Since self-citation represents a non-trivial component of all academic citations, as we show below, it is important to understand if there are systematic gender patterns in self-citations across a broad range of fields. To this end, we examine gender differences in self-citations across 1.5 million scholarly papers, with over a million self-citations. We then examine gendered self-citation patterns over time and between fields. We finish by discussing several possible mechanisms underlying these observations and the important implications of these findings for academic institutions.

METHODS

Self-citations: an author-to-author approach

Disambiguating authors—that is, determining when multiple papers are written by the same individual and when they are written by different individuals with the same name—is one of the major challenges in bibliometric analysis (Smalheiser and Torvik 2009). The JSTOR dataset is not disambiguated.³ To tally self-citations without author disambiguation, we assume that any citation to an author with the same name is a self-citation. There are a vast number of possible combinations of first and last names and a relatively small number of papers that will be cited as references on a paper in comparison. Given this, we feel it safe to assume that all but an inconsequential number of citations from an author John Smith to a published paper by a John Smith will be self-citations in their intended sense – meaning they were written by the same individual, not just by two individuals who just happen to have the same name.

A bigger problem is that, since we cannot track individual authors over time, we cannot control for differences in career stage or individual productivity. For example,

³ Disambiguation would highlight ties between papers by identifying when the same name belongs to the same individual across different authorship instances. We could have fully disambiguated the authors on a very small number of papers, but this would rule out assessing self-citation trends across many fields over time.

men authors may, on average, have more papers they can self-cite than do women authors. This could, in principle, generate a gap in self-citation rates even if men and women with the same number of published papers self-cite at identical rates.

When tallying self-citations, we consider all author-to-author citations, where a paper with four authors citing a paper with three authors counts as 12 author-to-author citations, one for each combination. An example: a paper written by four authors Pooja Gupta, Colin Jones, Armand Erickson, and John Williams (2010) cites a paper written by three authors Rita Juarez, Colin Jones, and Sarah White (2008). Colin Jones (but no one else) is an author on both papers. This citation represents 12 author-to-author pairs (Gupta to Paulson, Gupta to Jones, Gupta to White, Jones to Juarez, etc., etc.) of which one – Colin Jones to Colin Jones – is a self-citation. Thus 1/12-th of the author-to-author citations here is considered a self-citation. The fraction of author-to-author self-citations will always be smaller than or equal to the fraction of citations that can be considered as self-citations at the paper level. Our example illustrates this plainly. At the paper level, the sole citation listed, from Gupta, Jones, Erickson, and Williams (2010) to Juarez, Jones, and White (2008), is considered a self-citation because Colin Erickson is on both papers. In this example, while 1/12-th of the author-to-author citations are self-citations, 100% of the paper-level citations are self-citations.⁴

⁴ What if a woman author now has a hyphenated name due to marriage (e.g. Smith-

We define the **self-citation rate** as the mean self-citations per authorship (author-paper pair), based on author-to-author self-citations.⁵ Let a_g be the number of authorships and s_g be the number of self-citations for a given group (across a year, gender, etc.). So across a group of papers, the mean self-citation rate will be the total number of self-citations out of the total number of authorships:

$$\text{selfcitation rate}_g = \frac{s_g}{a_g}.$$

We calculate the relative rate of men's self-citation to women's self-citation as follows. Let a_w and a_m be the number of women and men authorships respectively. Let s_w and s_m be the number of women's and men's self-citations respectively. Now we answer the question: if we standardize women's self-citation rate to 1, at what rate k do

Johnson), but references an article written under her maiden non-hyphenated name (e.g. Smith)? Hyphenated names due to marriage are not of significant concern in our network dataset: there are only 51,270 authorships with hyphens (1.8% of the total), with only a fraction of these likely due to marital name changes.

⁵ The self-citation rate as defined here measures the fraction of the outgoing citations that an author makes that go to his or her other papers. It would be extremely interesting to look at the fraction of incoming citations that an author receives that come from his or her own papers, but without the ability to disambiguate authors we are unable to consider this metric in the present paper.

men self-cite? This is calculated by solving the following expression for k :

$$\frac{a_m \times k}{a_w \times 1} = \frac{s_m}{s_w}.$$

For the longitudinal analyses, the date of a self-citation is taken to be the citing year, rather than the cited year.

The JSTOR “network dataset”

JSTOR is a not-for-profit digital collection of scholarly documents ranging in time from the mid-sixteenth century to the present day. The JSTOR collection includes over eight million individual documents and over four million research articles, of which 1.8 million are linked by citation to other articles in the collection. We focus on these documents, which we call the JSTOR “network dataset,” because they are amenable to citation network analysis.

We include only papers written in or after 1779, the date of the first self-citation in the JSTOR corpus, reducing our analytical dataset to 1.5 million papers. Unless specifically noted in a figure or finding, we base our analyses on the years 1779 – 2011. Sometimes we report only the years after 1950 or 1970, when sample sizes from earlier periods would be too small to draw any meaningful conclusions.

There are a total of 3.6 million authorships in the network data set, and over 39 million author-to-author citations. There are 6.2 million unique citing-cited pairs of author-author citations in the network dataset. Therefore, out of the 39 million author-to-author citations, many pairs occur repeatedly (as might be expected when a paper cites

multiple papers by the same author). The network dataset also includes 8.2 million paper-to-paper citations. Of these, over three quarters of a million paper-to-paper citations are self-citations. Further detail for this dataset can be seen in Table 1.

Mapping the hierarchical structure of scholarly research

A prior analysis (West et al. 2013) used the hierarchical map equation (Rosvall and Bergstrom 2011) to create a nested hierarchy of all papers in this network dataset based upon citation relations among the papers. This hierarchical classification revealed the structure of fields, subfields, and ever-finer partitions down to the level of individual research topics. The hierarchical map equation algorithm determined the boundaries between groups at each level of the hierarchy. We manually assigned names to the field, subfield, and research topic groups that the algorithm revealed by examining the 50 most important papers in each of the groups (based on the number of citations to each paper).

The hierarchical map equation leverages the duality between compressing data and finding patterns in that data. When one compresses a night view image of a country, the major highways and cities are highlighted. We compress citation networks in a similar way. But instead of roads and cars, our map shows citation trails (when a paper cites a reference paper) and the ideas transmitted along those citation trails. After releasing a random walker on the network, the algorithm tries to minimize the description length of the random walk process. In areas of the network where the random walker spends extra time moving back and forth within the same group of papers, the algorithm assigns an “area code.” These area codes that the random walker reveals are fields of science. These methods have been vetted in the network science literature and consistently outperform

other community detection algorithms (e.g., Aldecoa and Marín 2013; Lancichinetti and Fortunato 2009; Šubelj, van Eck, and Waltman 2015). The open source code for running the hierarchical map equation is called *InfoMap* and can be found at MapEquation.org/code.html. In this paper, we use the Article-Level Eigenfactor (ALEF) (West, Rosvall, and Bergstrom 2016) as the underlying random walk process that the hierarchical map equation compresses. This is a modified version of PageRank that is customized for article-level citation networks and works well for ranking nodes and revealing hierarchical structure (Wesley-Smith, Bergstrom, and West 2016).

Determining gender of authors: the “analytic dataset”

To assign gender to first name, we use the methods of West et al. (2013), which relied on US Social Security Administration records (available at <http://www.ssa.gov/oact/babynames/>) to provide information about first names and corresponding gender. (We are therefore restricted to follow the US Social Security data in acknowledging only two genders.) Authors with first names that are associated with both genders, such as ‘Jody’ or ‘Shannon’ were dropped from the analysis. We assign gender to authors' names that appear in the top 1000 most popular names in any year from 1879 – 2012. We assume that we can confidently assign gender to author if the author's first name has the same gender at least 95% of the time in the Social Security database.

We extract the first names of authors from 1.5 million papers in the JSTOR network dataset. Disregarding authors with only first initials may exclude women authors disproportionately, particularly in early eras when women may have been more likely

than men to publish with initials to avoid potential discrimination. Since in any given era, gender-ambiguous names are more likely to be women (Liebersohn, Dumais, and Baumann 2000), this may slightly downwardly bias our appropriate assignments of women. Similarly, we were unable to classify names that were not in the top 1000 US Social Security Administration records for any year from 1879 – 2012. As a result, authors of some nationalities may be underrepresented in our data set. In a few rare cases, national differences may cause misleading assignments for non-US authors (e.g. ‘Andrea’ is typically a woman's name in the US but a man's name in Italy).

Table 1. Network and analytic dataset sizes based on various descriptors of papers, citations, and authorships. All data derive from JSTOR database; years 1779 to 2011 unless otherwise noted.

Dataset	Description	Value
Network dataset	Papers (including both citing and cited)	1,787,351
Network dataset	Unique citing papers that cite other JSTOR papers	1,388,431
Network dataset	Unique citing papers that self-cite	411,403
Network dataset	Paper-to-paper citations	8,227,537
Network dataset	Paper-to-paper citations that are self-citations	774,113
Network dataset	Author-to-author citations	39,402,992
Network dataset	Unique citing-cited pairs of author-to-author citations	6,268,789
Network dataset	Total authorships (paper-author pairs)	3,578,138
Analytic dataset	Papers with extractable author names	1,450,605
Analytic dataset	Unique citing papers with author names that cite other JSTOR papers	1,092,376
Analytic dataset	Authorships (paper-author pairs) with author names	2,787,833
Analytic dataset	Men authorships, 1779 to 2011	1,595,721
Analytic dataset	Women authorships, 1779 to 2011	448,386
Analytic dataset	Men authorships, 1950 to 2011	1,501,312
Analytic dataset	Women authorships, 1950 to 2011	435,396

papers
citations
authorships

As discussed above, an *instance of authorship* consists of a person and a paper for which the person is designated as a sole or co-author. There are 3.6 million authorships in the JSTOR network dataset; of these, we were able to extract a full first name for 2.8 million authorships (77%). We were able to confidently assign gender to 73.3% of these authorships with full first names, including 1.6 million men and nearly 0.5 million women. The remaining authorships involve names not in the US social security lists (24.3%), or names associated with both genders (2.4%). The final analytic dataset includes all papers where we know the gender of one or more authors. The values for these different data types – and others – can be seen in Table 1.

Bootstrapping Standard Errors

We calculate self-citation rates for men and women across a large number of authorships and then take the ratio of these rates in each year in our network dataset. To estimate confidence intervals for these ratios, we use a bootstrap approach and resample at the level of individual papers. Essentially this amounts to resampling papers, with replacement, from the appropriate set and calculating our statistic of interest on the total of all authorships within all resampled papers. To ensure accuracy, two different authors coded all but one of these bootstrap simulations separately in two different programs, Stata/IC 13.1 for Mac and Mathematica 10.1 for Mac.

Let the ratio of men’s self-citations to women’s self-citations be k :

$$k = \frac{s_m/a_m}{s_w/a_w} = \frac{\bar{x}}{\bar{y}},$$

where we denote the men’s self-citation rate by \bar{x} and women’s self-citation rate by \bar{y} .

For each year or field, then, our original sample contains m men and w women. We then

draw n bootstrap samples, each with m men and w women selected with replacement from the original data. For each bootstrap sample i , we compute the men's self-citation rate \hat{x}_i and the women's self-citation rate \hat{y}_i . Next, for each \hat{x}_i and \hat{y}_i we compute the bootstrap ratio \hat{k}_i :

$$\hat{k}_i = \frac{\hat{x}_i}{\hat{y}_i} \text{ for all } i = 1, \dots, n.$$

We then order all \hat{k}_i such that $\hat{k}_i \leq \hat{k}_{i+1}$, and find the value of \hat{k}_i at the 2.5th percentile and the 97.5th percentile of n . These values are the lower and upper bounds of the 95% bootstrap confidence interval, respectively, for that year. For example, if $n = 10,000$, after sorting the values in ascending order, the 2.5th and 97.5th percentiles of the distribution fall at positions 250 and 9,751.

The SSRN Dataset: Additional Verification of the Gender Gap

To provide another test of our findings, we look at self-citation by gender in another, smaller set of papers: the Social Science Research Network (SSRN) dataset. This dataset is unusual in that the authors have been carefully disambiguated (see West et al. 2013): we can distinguish for example between one individual Rita Juarez who has written two papers, and two individuals named John Williams, each of whom have written one. The SSRN dataset includes 426,412 papers (including pre-prints) from 99,465 authors, with more than 2.4 million citations among those papers. In addition to being smaller, the SSRN dataset differs from JSTOR because authors voluntarily upload papers to SSRN.

We follow the same procedure for gender assignment as with the JSTOR data

Men account for 73% (38,265) of authors who can be disambiguated by name and whose gender can be identified, while women account for 27% (14,379). We can identify a gender for a total of 10,212,014 authorship-to-authorship citations. Men authors have 280,818 papers with 181,742 self-citations, for an average of 0.647 self-cite per paper. Women authors have 68,256 papers with 28,075 self-citations, for an average of 0.411 self-cite per paper. Among all authors, including those with zero self-citations, men self-cite an average 0.193 and women 0.128 times per paper.

RESULTS

How common is self-citation?

To provide more context for the importance of self-citation, we wanted to know: what proportion of citations in an article are self-citations, on average? This helps to address the relative importance of gender disparities without disambiguating author names. Within all papers in the JSTOR corpus, 774,113 paper-to-paper references were self-citations. Among all 8.2 million references, then, 9.4% are self-citations: references that cite a previous paper authored by one or more of the present paper's author(s). Put another way, across all fields and years, about one in 10 references is a self-citation.⁶

Figure 1 presents these results broken down by major academic field. Molecular biology has the highest self-citation rate per reference, while classical studies has the lowest. There is no notable correlation between this self-citation rate and the gender ratio of authors in the field, as we discuss in more detail later.

⁶ Within only those papers that included self-citations, there were a total of 3,754,942 references. Among only these papers that cite earlier papers written by their same authors, then, approximately 21% of included references are self-citations!

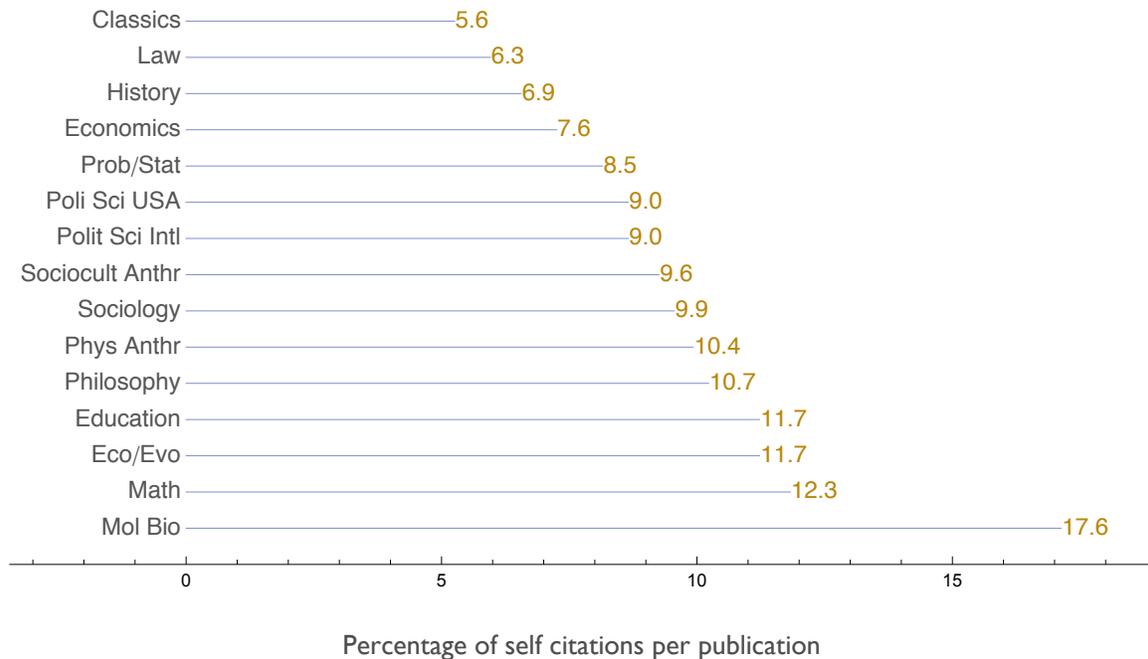


Figure 1. Mean percentage of self-citations per publication by field in JSTOR, 1779-2011. Shown here is the percentage of a paper’s references that cite papers written by that paper’s author(s), averaged across each major field. A value of 10 means 10% of a paper's citations are references to paper(s) previously written by the paper's author(s).

The paper with the most self-citations by its authors is a report in *Science* entitled “A Comparison of Whole-Genome Shotgun-Derived Mouse Chromosome 16 and the Human Genome.” In no sense is this an example of excessive self-citation; the paper references only four previous papers written by any of the paper’s 175 authors. But because three of the cited papers each have many authors from the citing paper, the authorship-to-authorship links add up to 220 self-citations. Another example is a paper in the *American Economic Review* entitled “Information and the Change in the Paradigm in Economics.” This is single-authored paper with 70 self-citations out of 130 references. This is certainly not a case of excessive self-citation either: the paper is an adaption of Joseph Stiglitz’s Nobel Prize lecture, the whole point of which is to trace the arc of his

career.

These two papers illustrate alternative paths to the same end: at one extreme, papers with many authors citing even a few papers with many of the same authors; at another extreme, sole-authored papers citing many previous papers. These different effects may be differentially likely in different fields. Note, however, that additional analyses (results not shown) did not suggest any notable relationship between the number of references cited by a paper and the number of self-citations.

Self-citation can be an influential force in raising an academic's citation count. For a powerful example, consider one prominent scholar—listed by Thomson-Reuters as one of its Highly Cited Researchers—with nearly 7000 Web of Science citations. Of these, over 1500 are self-citations. On average each of this author's over 290 papers cites slightly more than 5 of his previous papers. As a result, this scholar receives nearly 22% of his citations from himself—even ignoring the additional citations from others that are generated by preferential attachment processes (Fowler and Aksnes 2007). This is obviously an extreme case, and we do not want to demonize the practice of self-citation.⁷

⁷ For example, the present paper will provide the authors with 1, 5, 3, 1, and 4 self-citations respectively by authorship order – and while we believe that none of the self-citations herein are extraneous, we note that the men authors of this paper cite themselves at nearly three times the average rate of the women authors.

But we do want to emphasize how common self-citation is, along with the profound effect it can have on an academic's citation count.

Self-citation patterns by gender

Between 1779 and 2011, there are 1,595,721 men authorships and 448,386 women authorships in our analytic dataset. Men represent 78.1% and women 21.9% of authorships for which we could identify the gender, dating back to 1779. Dating back to 1950, there are 1,501,312 men authorships and 435,396 women authorships. Since 1950, men represent 77.5% of the authorships for which we know the gender, and women make up the remaining 22.5%.⁸ Moving the start of the window from 1779 to 1950, then, we see a change in the authorship gender gap by less than one percentage point. The change is so slight because JSTOR contains comparably few documents dating to before 1950.

Because papers often have more than one author, there are more author-to-author citations than paper-to-paper citations. In the analytic dataset, there are 1,017,362 author-to-author self-citations. Of these, there are 678,768 self-citations by men, 121,923 self-citations by women, and 216,671 self-citations by authors of unknown gender. This means that of the self-citations for which we know the author's gender, men are

⁸ There were 743,319 authorships for which we could not identify gender. See West et al. (2013) for more details on the method we followed.

responsible for 84.8% of the self-citations while women are responsible for 15.2% of the self-citations.

Standardizing women's self-citation rate to 1.0, we solve for the ratio of men's self-citations relative to women's for the years 1779 to 2011:

$$\frac{\% \text{ men authorships} \times \text{men's selfcite rate } k}{\% \text{ women authorships} \times \text{women's selfcite rate}} = \frac{\% \text{ men's selfcites}}{\% \text{ women's selfcites}}$$

$$\text{or } \frac{78.1 \times k}{21.9 \times 1} = \frac{84.8}{15.2}$$

Solving for k , we find a ratio of 1.56, meaning that the average man self-cites 56% more often than does the average woman. This is remarkably consistent with the results reported by Maliniak and colleagues (2013), who analyzed 3000 articles from the field of international relations and reported that men authors self-cite 60% more often than women authors. (Using the JSTOR network dataset, we find that men self-cite their own work 58% more often than women in the field of domestic political science and 68% more often in international political science.)

Next we visualize the total number and fraction of self-citations by author gender. We look at absolute numbers rather than the percentage of a paper's citations that are self-citations because there are many papers with one citation that is a self-citation; visualizing the percentage of citations that are self-citations results in long tails and does less to further our understanding.

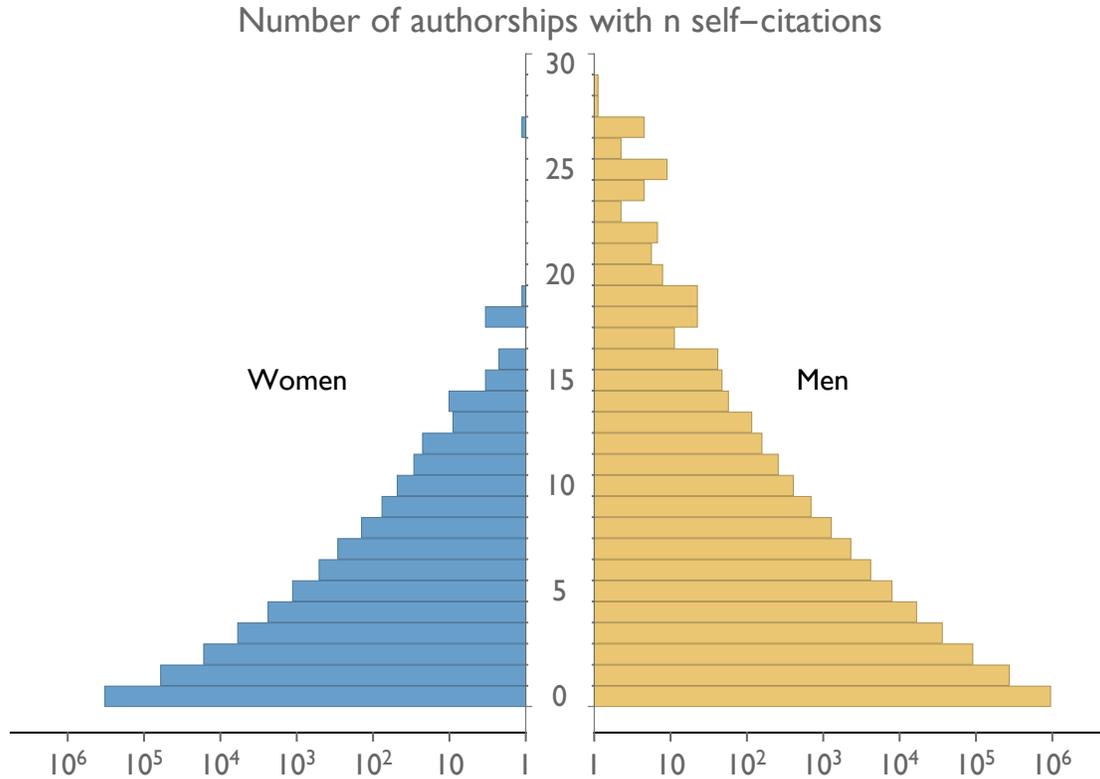


Figure 2. Number of authorship instances where specified number of self-citations occurs, by gender in JSTOR, 1779-2011. Each bar's length (along the horizontal axis) is equal to the log number of observations of n self-citations (on the vertical axis).

In how many papers do men and women authors cite themselves n number of times? Figure 2 shows the log frequency of self-citation counts by gender for each number of self-citations. Men have higher counts in all categories of numbers of self-citations, including papers with no self-citations. Since there are more instances of men authorship in the network dataset, this is not surprising.

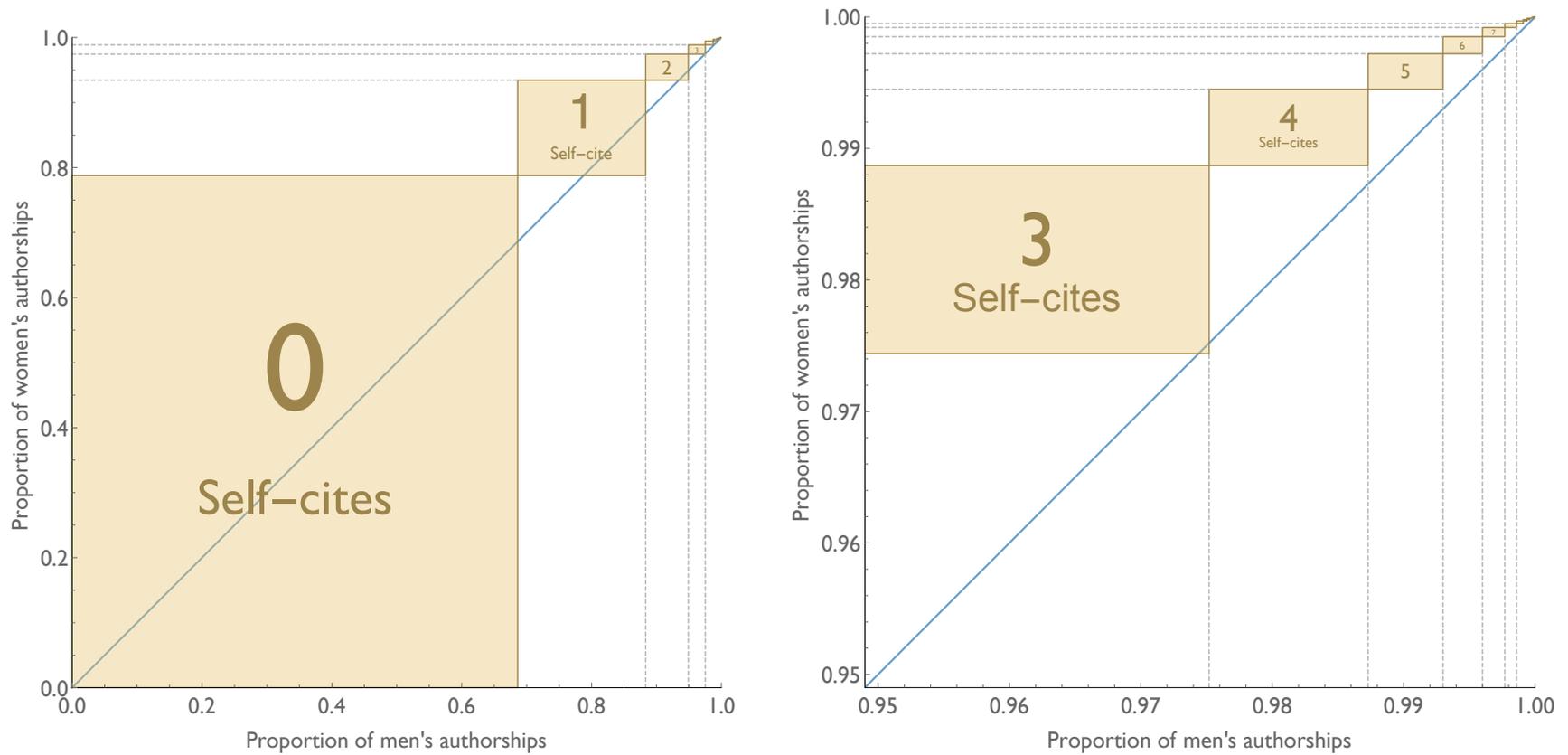


Figure 3. Proportion of authorship instances where specified number of self-citations occurs, by gender in JSTOR, 1779-2011. The first half of the figure shows the whole range of possible numbers of self-citations, while the second half zooms in on the area representing 3 self-citations and above. The right edge of each box indicates the proportion of men who cite themselves that number of times, while the upper edge of each box indicates the proportion of women who cite themselves that number of times. The diagonal line represents the point of gender parity, which would bisect the corners of the boxes if the genders behaved identically in patterns of self-citation.

However, Figure 3 shows us that relative to men's authorships, women's authorships are more likely to feature zero self-citations. Women cite themselves one or more times in their papers less often than men do. In other words, compared to men, women are over-represented in the zero self-citations category and underrepresented in terms of citing their papers at all.

Figure 3 shows self-citations grouped by proportions of men's and women's authorships. This shows the rank (1st percentile, 20th percentile, 99th percentile, etc.) in terms of self-citation proportion on the x-axis for men and what rank that same author would have if he were instead part of the women's distribution of authorships on the y-axis. If men and woman behaved similarly in their approaches to self-citation, the corners of the boxes should plot a curve along the x-y diagonal. Instead, wherever there is a difference in the proportion of men and women citing themselves a certain number of times, the corners of the boxes deviate from the diagonal.

For example, if in a paper you never cite another paper of your own, you are among the vast majority of men (68.6%) and women (78.8%) who do not cite themselves. If you have one self-citation, you are in the 68th to 88th percentile range for men but the 78th to 93rd percentile for women. With four self-citations in a single paper, a woman is in the 99th percentile, while a man is in the 98th.

Understanding these distributions is important because they help us see that the gendered nature of self-citation averages is not a result of highly skewed tails representing aberrant behavior. It is the product of the daily activity of the vast majority of academics, those who cite themselves in their papers fewer than five times.

Self-citation rates over time

The very first self-citation in our dataset was in 1779 to a paper dated 1773. Edward King, in his paper “Account of a Petrefaction Found on the Coast of East Lothian,” cites his own previous “A Letter to Mathew Maty, M.D. Sec. R S.; Containing Some Observations on a Singular Sparry Incrustation Found in Somersetshire” (King 1773, 1779).

Figure 4 shows the self-citation ratio for each year. In the 1950s, the relative rate⁹ of men's self-citations relative to women's self-citations was 1.23. However, during the 1950s, the bootstrapped 95% confidence intervals of the annual ratios overlap with an

⁹ The relative rate is calculated by first summing the total number of self-citations by men (or women) across the decade, then dividing this by the sum of the total number of men (or women) authorships across the decade:

$$\text{Men's 1950s rate} = \frac{\sum_{1950}^{1959} S_y^M}{\sum_{1950}^{1959} A_y^M}$$

where S_y^M is the number of self-citations by men in year y , and A_y^M is the number of men authorships in year y .

The men's rate for the decade is then divided by the women's rate for the decade to give the relative rate. This is important because the sample sizes differ in each year and because the relative contribution of each year may differ for men and women. We compute the average rates across the decade for each gender and only then take their ratio.

equality ratio of 1.0, indicating that we cannot reject the null hypothesis of gender equality in self-citation rate during this decade. However, beginning in the 1960s, the ratio of men's to women's self-citations per authorship remains steadily significantly above 1.0. In the 2000s, the relative rate was 1.71. There is no evidence that the gender gap is decreasing over time.

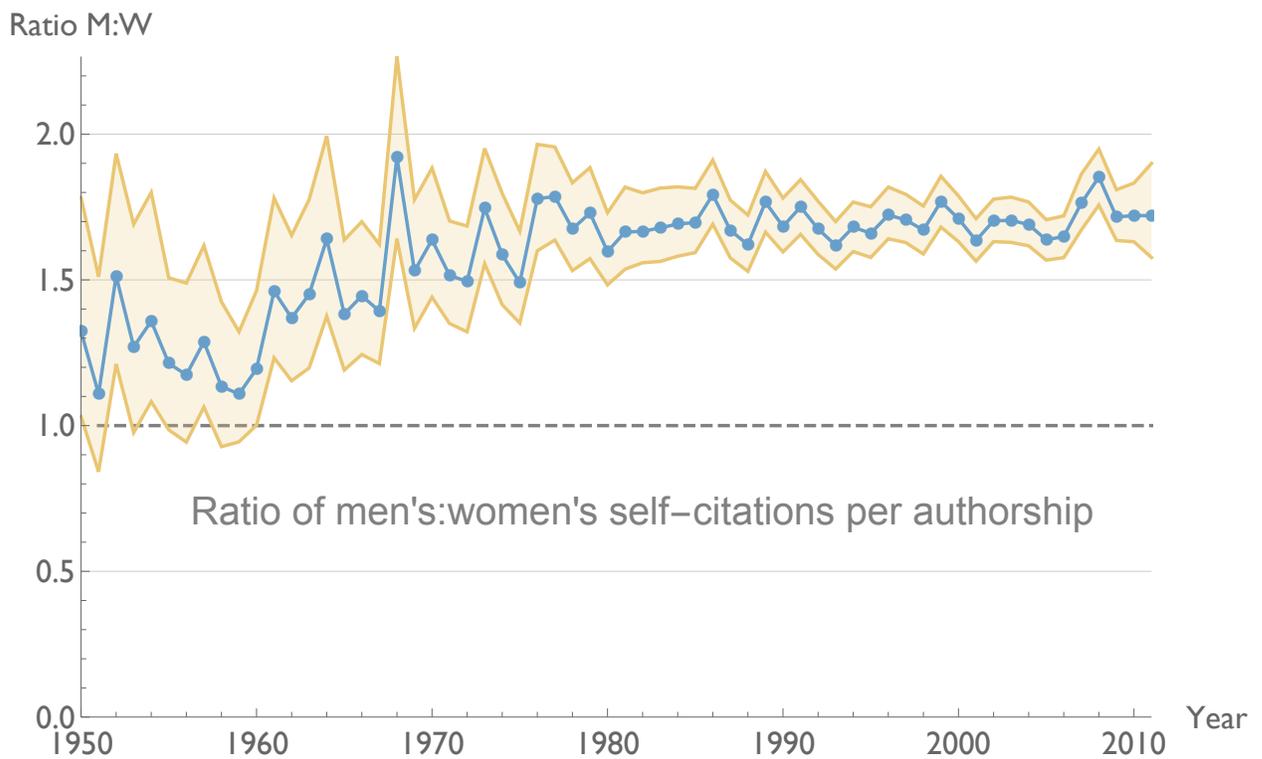


Figure 4. Men cite themselves more than women do. Shown here, the ratio of men's self-citations per authorship relative to women's self-citations per authorship, for JSTOR articles over the period 1950 to 2011. If men and women cited themselves at equal rates, the ratio shown would be 1.0. A value of 1.5 means that men cite themselves 50% more than women in papers published during that year. Shaded intervals represent 95% bootstrap confidence limits.

Since the ratio is composed of the relative rates of men's and women's self-citations, we wondered what the patterns underlying this trend might be: Do both men

and women self-cite at increasing rates? Or are the rates for each gender relatively steady over time? To investigate this, we plotted men's and women's self-citation rates separately over time (Figure 5).

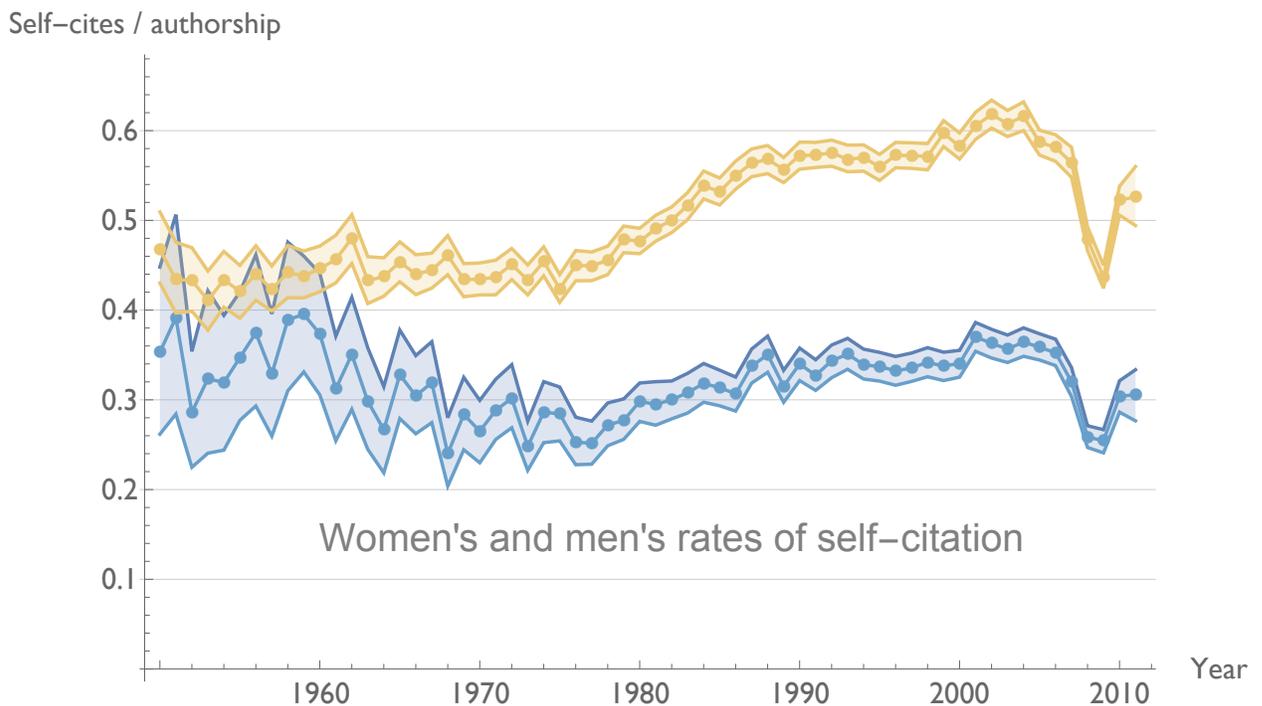


Figure 5. Men's rate of self-citation has been higher than women's since the 1960s. Shown here, the mean number of men's self-citations per authorship (yellow line) and women's self-citations per authorship (blue line), for JSTOR articles over the period 1950 to 2011. Shaded intervals represent 95% bootstrap confidence limits.

Beginning in the 1960s, men had a consistently higher rate of self-citation than women did, across all fields. Note that the sharp drop after 2006 is likely due to the blackout window for certain fields (some papers do not appear on JSTOR until 5 years after publication), combined with differences in self-citation rates across fields.

Self-citation rates by field

Although the average ratio shows that men cite their own papers more than women, self-citation behavior varies widely across fields and subfields. Figure 6 shows men's and women's self-citation rates by major academic field. Each and every field in the plot reveals a large and significant difference between women's and men's self-citation rates.

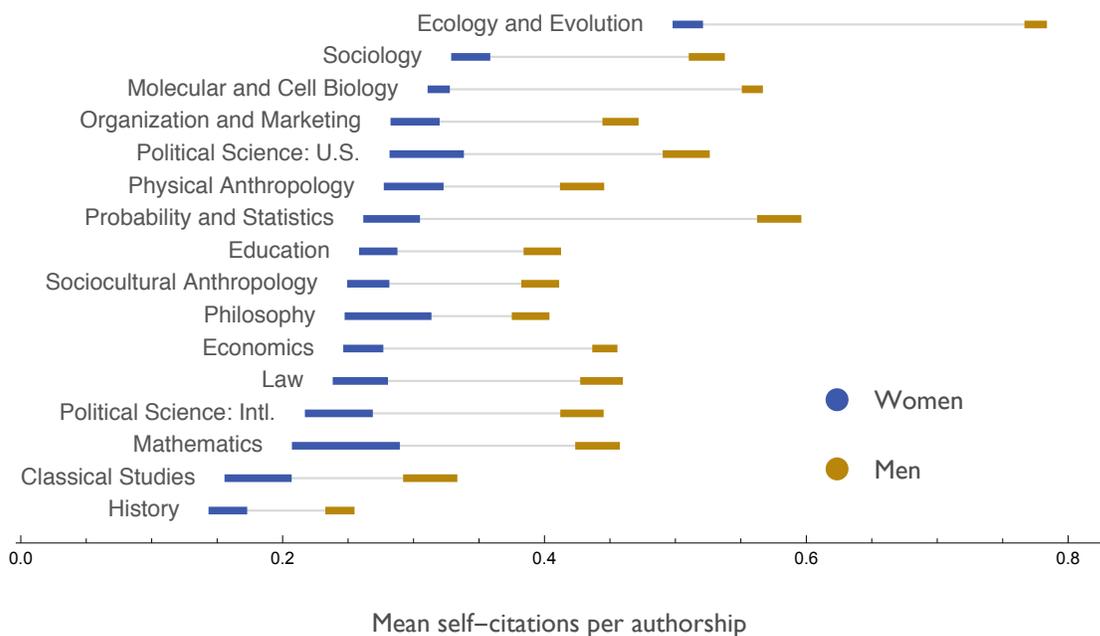


Figure 6. Mean number of men's self-citations and mean number of women's self-citations per authorship across major fields, based on author-to-author self-citations, in JSTOR, 1779-2011. Orange numbers represent men's average number of self-citations per authorship in that field, and blue numbers represent women's average number of self-citations per authorship. Dark colored bars represent 95% bootstrap confidence intervals for each gender.

Previous research found that women's disadvantage in garnering citations decreased as women made up an increasingly large proportion of the field of economics (Ferber and Brün 2011). We wondered whether the gender composition of a field's authorships might correlate with the rate of self-citation. The fields with the lowest

women's self-citation rates per authorship (and their corresponding proportions of women authorships in each field from 1779-2011) are history (22.5%) and classical studies (22.3%). The fields with the highest women's self-citation rates per authorship are ecology and evolution (19.4%), sociology (32.9%), and molecular and cell biology (26.8%). Under a linear model there is no significant relationship between women's (or men's) self-citation rate per authorship and the proportion of authorships that are women in a field.¹⁰

Figure 7 shows the relative self-citation ratios at the field level. For each of these 16 largest fields, we also display the ratios for the subfields determined by the hierarchical map equation algorithm. Even within each major academic research field, gender ratios of self-citation vary depending on the subfield. Some subfields fall above the line indicating a ratio of 1.0, indicating women self-cite more on average than men in that subfield. So that readers can explore these results for themselves, we present self-citation rates by gender across research domains in an interactive data visualization at <http://www.eigenfactor.org/projects/gender/self-citation/index.html>.

¹⁰ It is possible that what might matter more than a continuous level is some threshold level at which women are no longer considered tokens in the workplace (Cain and Leahey 2014; Kanter 1993). Though our measure is a continuous one, our analysis shows no evidence of a threshold effect here, either. Results available on request.

Teacher efficiency: .76		Dance ethnology: .29	Perception: 52		
College biology: .90	Maritime hunter-gathers: 72	Kinship and descent in Samoa: 75	Natural language: 64	Adam Smith: 77	
Study and learning: 1.04	Human behavioral ecology: .95	Native Americans of the Northwest: .83	Logic and mathematics: .90	Literacy in Britain: .82	
Teacher development: 1.08	Hunted fauna: 1.01	Concept of the self: .98	Diophantine problems: .94	Technology and telephony: .86	
Self-image and performance : 1.10	Early civilizations: 1.12	Spirit possession and shamanism: .99	Naturalistic metaphysics: .94	Japanese anti-imperialism: .87	
Minority students: 1.10	Southern Africa: 1.13	Japan: 1.00	Economic anthropology: 1.07	17th century religion and society: .88	
Mathematics instruction: 1.21	American Southwest: 1.14		New Guinea: 1.09	Colonial America: .90	
Gender roles and education: 1.27	Theoretical archeology: 1.18		Epistemology: .97	Gender: .80	Osmotic regulation in fish: 1.04
Early work in early reading: 1.30	Native American social structure: 1.32		Causality: .99	Native Americans and Christianity: 1.03	Haplodiploid sociality: 1.24
Education: 1.30	Physical anthropology: 1.34		Anti-individualism: 1.0	Public history: 1.09	Herpetology: 1.27
Student learning: 1.35	Origin of agriculture: 1.46		Intention: 1.04	Slavery and agriculture: 1.09	Aquatic ecology: 1.36
Reasoning acquisition: 1.42	Settlement of the Americas: 1.46		Probability and belief: 1.08	Early modern political philosophy: 1.21	Spiders: 1.37
School effectiveness: 1.46	Human origins: 1.51		Metaling: 1.11	Vagueness: 1.25	Phylogeny: 1.39
Small-group learning: 1.49	Archaeology: 2.29		Culture change: 1.28	American exceptionalism: 1.25	Population genetics: 1.41
Learning disabilities assessment: 1.59	Settlement of Oceania : 3.86		Indonesia: 1.29	Postmodern history: 1.31	Plant ecology: 1.43
Early work in socialization: 1.61	Native depopulation: 3.89		Native American social structure: 1.32	British economic history: 1.32	Evolutionary ecology: 1.43
Testing: 1.61			Philosophy: 1.37	Physiology: 1.38	Ecology and evolution: 1.44
Arithmetic: 1.84			Physical anthropology: 1.34	Early modern England: 1.48	Arthropods: 1.47
Media role and influence: 1.92			Hunting territories: 1.47	Writing history: 1.82	Paleontology: 1.58
Scientometrics of education: 2.51			Tricksters and conflict: 1.48	Abolitionism: 1.85	Mammology: 1.61
Learning channels: 2.77			School effectiveness: 1.46	Progressive era American populism: 1.89	Lichens and bryophytes: 1.63
Meta-analysis and assessment: 3.19			Human origins: 1.51	American studies: 1.94	
			Archaeology: 2.29	Irish American slavery: 1.51	
			Settlement of Oceania : 3.86	American industrialization: 1.53	
			Native depopulation: 3.89	Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	
				Eighteenth century France: 1.69	
				Frontier history: 1.79	
				Writing history: 1.82	
				Abolitionism: 1.85	
				Progressive era American populism: 1.89	
				American studies: 1.94	
				Irish American slavery: 1.51	
				American industrialization: 1.53	
				Class in 19th century Britain: 1.55	

Self-citation rates by field over time

We also looked at the changes in the self-citation rates and ratios within fields across time. This helps ensure our results are not an artifact of the different norms for self-citation in different disciplines combining with different proportions of men in each discipline.

If we look over time, we again see a consistent gender gap within each field. Figure 8 illustrates self-citation ratios across time for ecology and evolution, molecular and cell biology, economics, and sociology. Because the sample sizes for individual fields are substantially smaller than those for the entire corpus and because confidence intervals for ratios are sensitive to small sample sizes, we restrict our visualization to the most recent 40 years, for which we have the most data. For these four largest fields for which we have the best longitudinal data in the JSTOR dataset, gender inequality in the self-citation ratio persists across the 40 years shown.

We also break down the rates of self-citation for men and women by the top 16 largest fields (Figure 9). The confidence intervals for the individual rates are naturally tighter than those for their ratios. Here we see that men's self-citation rate is generally higher than women's self-citation rate across time. In the fields (such as mathematics) and time periods (prior to 1970) with fewer papers, the confidence intervals do overlap more.



Figure 8. Gender ratios of self-citation rates across time for the four largest fields. The ratio of men's self-citations per authorship relative to women's self-citations per authorship, in the four largest JSTOR fields of Ecology and Evolution, Molecular and Cell Biology, Economics, and Sociology over the period 1970 to 2011. If men and women cited themselves at equal rates, the ratio shown would be 1.0. A value of 1.5 means that men in that field cite themselves 50% more than women in papers published during that year. Shaded intervals represent 95% bootstrap confidence limits.

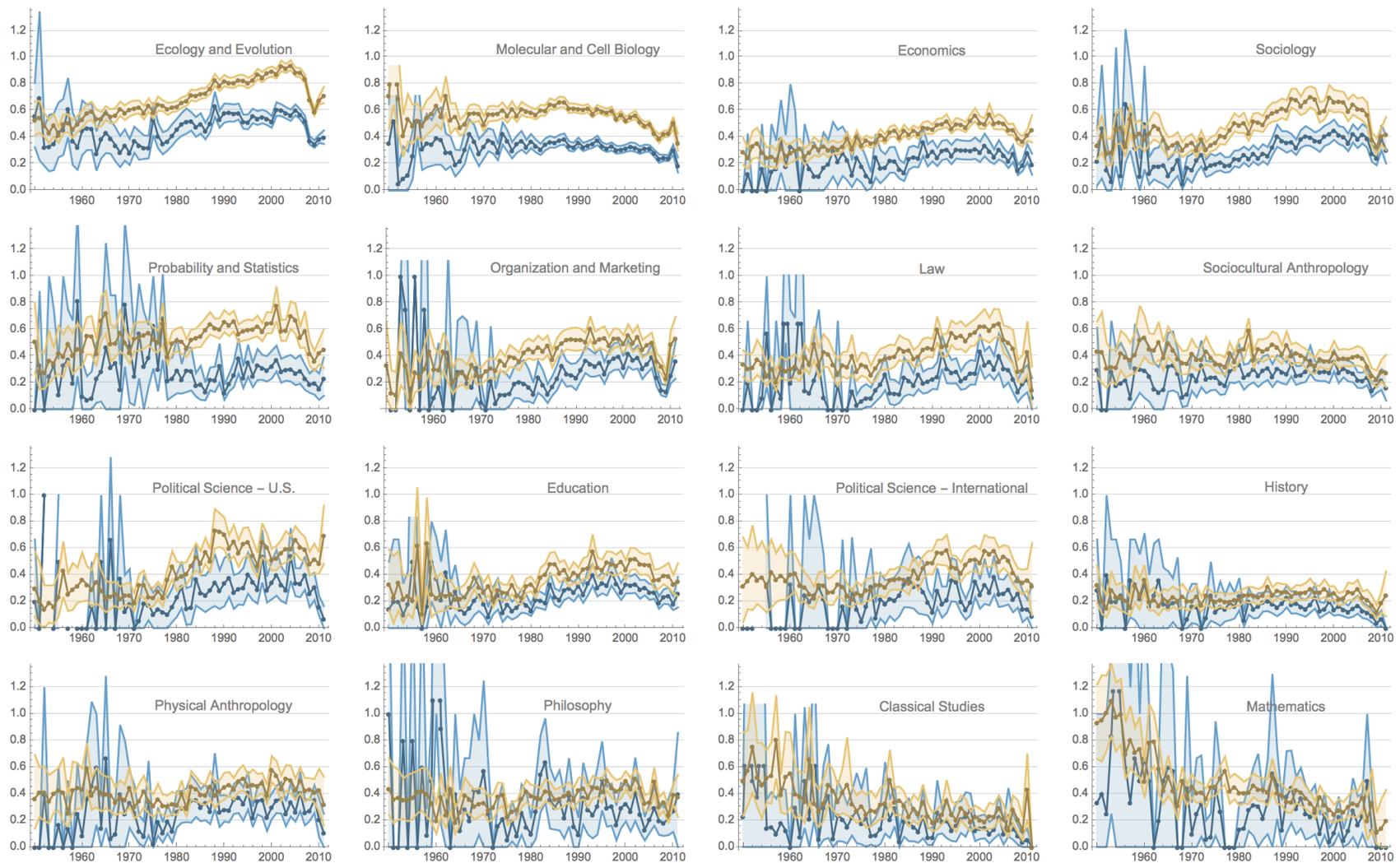


Figure 9. Men consistently self-cite more than women across fields. Shown here, the mean number of men's self-citations per authorship (yellow line) and women's self-citations per authorship (blue line), for the 16 largest fields in the JSTOR dataset over the period 1970 to 2011. Shaded intervals represent 95% bootstrap confidence limits.

Self-citation rates by size of author team

We wondered whether the tendency of men and women to collaborate and coauthor at different rates (Abramo et al. 2013; Bozeman and Gaughan 2011) and the lower likelihood of women to write sole-authored papers (West et al. 2013) might play any role in the gender differences in self-citation rates. To explore this, we looked at the differences in the mean number of self-citations per authorship across papers with one to twenty authors. Figure 10 illustrates that those with sole-authored papers and with smaller teams of collaborators have a higher mean number of self-citations. Author-to-author self-citations occur at lower rates in papers with more authors. However, we noticed no interactions with gender.

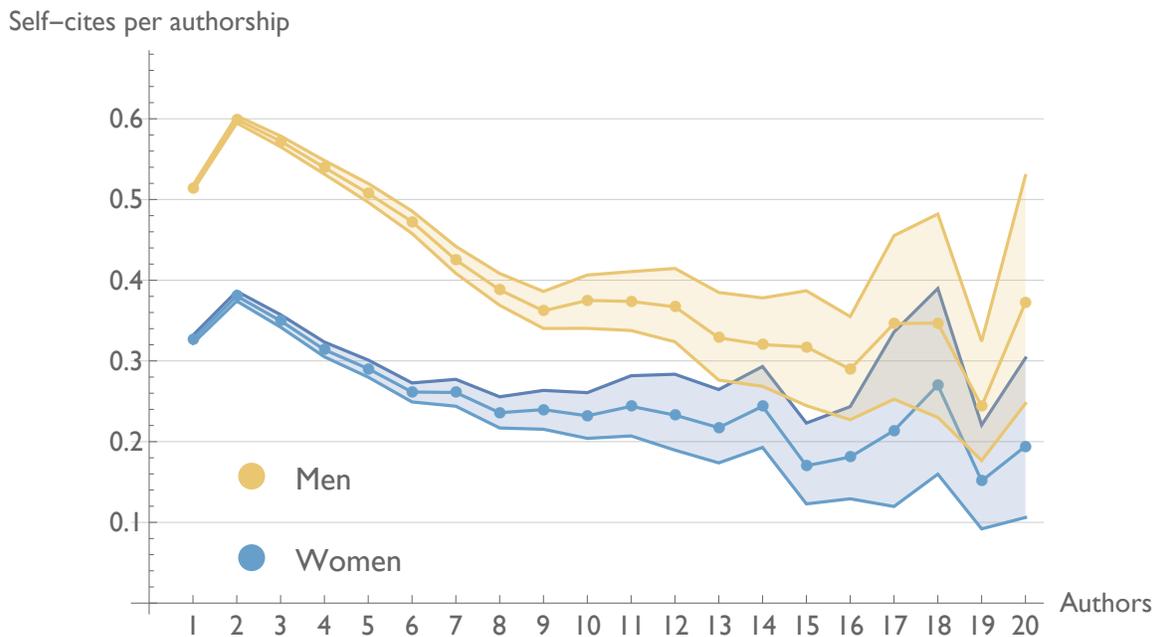


Figure 10. Mean number of self-cites per authorship by the number of authors on a paper, in JSTOR, 1779-2011. We truncate the results at 20 authors because, given small sample sizes, the data become excessively noisy beyond that threshold. A value of 1.0 on the vertical axis indicates that, on average, each author cites one of his or her previous papers in the current paper. Shaded intervals represent 95% bootstrap confidence limits.

DISCUSSION

Our study uses an unprecedentedly large dataset of 1.5 million papers across a broad range of academic fields to examine trends in self-citation by academic researchers. Examining 39.4 million author-to-author citations and over 1 million self-citations in the JSTOR database, we uncovered a number of important patterns:

- (1) About 9.4% of all citations are self-citations that reference previous papers written by one of or more of the current paper's authors. This indicates that self-citations have the potential to make up an important fraction of all citations to authors' work.
- (2) Compared to women, men are more than ten percentage points more likely to self-cite (21.2% of women authorships vs. 31.4% of men authorships self-cite). Still, the majority of authors never cite themselves in a given paper.
- (3) In the last two decades of our data, men have cited themselves at 1.7 times the rate of women.
- (4) There is wide variation across fields and subfields, but we do not observe any obvious relationship between the proportion of women in a field and the relative rates of women's and men's self-citation in that field.

We now turn from our findings to speculate on possible mechanisms that might underlie these important trends, before finishing with a discussion of their consequential implications.

Potential Mechanisms

Why might men academics cite their own previous work more than women

academics? While our JSTOR data include a large number of papers and self-citations, they do not contain variables that allow us to determine the cause of the patterns we identify. However, prior research suggests several mechanisms that are consistent with our results.¹¹ We review five mechanisms here, which potentially contribute to the gender self-citation gap:

- (1) Men may self-cite more because they evaluate their abilities more positively than women.
 - (2) Men face fewer social penalties for self-promotion.
 - (3) Men specialize more in academic subfields, and specialization may encourage
-

¹¹ Edward King (1779), in the aforementioned first-ever self-citation paper in the JSTOR corpus, provides the amusing warning and commentary: “We should not venture, it is true, without great caution, to speculate on these matters, as hasty and specious conclusions may easily be drawn by any one who indulges too readily a quick and lively imagination, which will ever be too ready to mislead, rather than to procure solid information. But though I am well aware of this danger, yet I venture to lay before you these few observations... for they are not made merely in consequence of a flight and hasty survey of this one specimen, but are in truth conclusions that I have been led to form incidentally in the course of a very long inquiry...” So, too, do we venture to speculate based on thorough observations combined with a long course of study.

more self-citation.

(4) Men publish more papers, particularly earlier in their careers, and therefore have more work to cite.

(5) Men publish different types of papers; namely, the types of papers an academic may be more likely to self-cite.

We describe the existing evidence for each in turn.

The first two mechanisms – women’s lower self-assessments of their accomplishments and greater social sanctions against women who self-promote – are related. Status beliefs about gender shape men’s and women’s behavior and expectations of themselves and others (Ridgeway 2001, 2014). Because women are perceived as lower status, they are often evaluated more negatively than equally qualified men candidates, by women as well as by men (Moss-Racusin et al. 2012; Reuben, Sapienza, and Zingales 2014). Women evaluate their own abilities more critically, even when faced with evidence of equivalent performance (Correll 2001, 2004). Women are especially prone to be evaluated critically (Cech et al. 2011; Thébaud 2010) or penalized for success (Heilman et al. 2004) when working in male-dominated domains. However, recall that we did not find that women self-cited less in more men-dominated fields. We found no relationship between the proportion of men in a field and the likelihood that a woman will self-cite. However, academia overall is male-dominated. If social sanctions for self-promotion are playing a role in women’s lower likelihood to self-cite, then, at least according to our results, they are likely exerted in a more generalized way; i.e., women are being sanctioned within academia or society as a whole, rather than by field.

When women seek to actively establish their competence by self-promoting, they often experience backlash from both men and women (Rudman et al. 2012). Gendered perceptions of self-promotion likely influence perceptions of self-citation, which could be viewed as a form of self-promotion in the academic workplace. Women are less likely than men to negotiate for what they want in the workplace. Men are also more likely to receive the corresponding rewards from these negotiations, such as higher salaries (Babcock and Laschever 2007; Babcock et al. 2003). Status expectations are particularly likely to operate in ambiguous contexts where evaluation criteria are subjective and loosely defined (Fox 2001; Ridgeway 2011) – such as those surrounding evaluations of the importance of an academic paper.

Field segregation by gender may also contribute to gender discrepancies in self-citation rates, for two reasons. First, fields have different norms around self-citation. Self-citation rates are higher in the natural sciences (Snyder and Bonzi 1998). We might expect to find higher self-citation rates in fields with more men authors. However, this is not the case: comparing across fields, there is no significant correlation between the mean number of self-citations per paper and the fraction of men authors in a field. Second, men tend to specialize more within their academic fields, at least within the disciplines of sociology and linguistics (Leahey 2006); this more specific focus may encourage self-citation. A research strategy where a scholar is focusing on building on previous work would likely result in many more self-citations. One remaining question for future research is whether specialization might explain gender differences in self-citation tendencies; we hope to test this in future work.

In part because men specialize more (Leahey 2006, 2007), they tend to produce

more total papers per year in most fields (Barnett et al. 1998; Bentley and Adamson 2004; Cole and Singer 1991; Fox 2005), particularly earlier in their careers (Long 1992). Not only does higher productivity lead to more papers for scholars to self-cite; more productive scholars also generate more highly cited papers (Symonds et al. 2006). Differences in productivity might cause or further exacerbate gender inequality in self-citation counts.¹² The ratio of women to men individuals present in academic careers

¹² Here is a highly simplified example of how we could get the results above *without any difference in self-citation behavior*. Suppose men and women behave the same, such that there is no gender-differentiated effect of self-promoting behavior (mechanism 1) or social sanctions for self-promotion (mechanism 2). Imagine that everyone cites everything they have ever written in every paper they write. But suppose the distribution of paper counts differs. All women only ever write two papers, while all men only ever write three. In this example, the average number of self-citations per authorship for men is 1 (each man cites his first paper in his second paper, and his first two papers in his third paper, for a total of three self-citations across three papers). The average number of self-citations per authorship for women is 0.5 (each woman cites her first paper in her second paper, for a total of one self-citation across two papers). The gap in overall self-citation rates would diminish with increasing numbers of papers, but as long as men published even slightly more papers – on average – than women, and both self-cited at the same

decreases as we climb up the academic status ladder. Attrition out of the academic pipeline means that women have fewer papers to self-cite and fewer later opportunities to do so, in aggregate in our dataset.¹³ This is a corollary of the productivity mechanism because men will have overall greater productivity throughout their careers. However, we do not see a trend toward equality in women's and men's self-citation rates over time, despite the increase in the number of women in more senior academic positions in many fields. We would expect this demographic shift to result in more papers for these senior women to self-cite. But our observations do not indicate any decrease in the self-citation gap over the last 50 years.

Finally, there are also differences in the types of papers produced by men and women; for instance, women are significantly underrepresented as authors of single-authored papers and – on papers with three or more authors – in the prestigious positions of first and last author (West et al. 2013). These types of papers may constitute the kind

rates, there would always remain a difference in the average self-citation rates by gender.

¹³ For example, in our dataset, a higher proportion of the women represented may have gone on to non-academic careers than the men in our dataset. If this were the case, those women who published as PhD students or as young researchers would not have had as much opportunity to self-cite later in their careers as the men who stayed on to become career academics.

of work that would be in the authors' core areas of research interest, and thus papers they may be more likely to self-cite. Publishing with a larger team of coauthors also reduces the mean number of self-cites per authorship (Figure 10). Since women are not publishing single-authored papers as often as men (West et al. 2013), they are likely to have fewer self-citations per authorship. Overall, however, it may be that those types of papers that women tend to publish disproportionately fewer of are also those that attract more self-citations.

We conducted a preliminary evaluation of an additional, smaller, less representative dataset, the Social Science Research Network (SSRN) database. The SSRN is a pre-peer review voluntary archive. With this dataset, we find a gender self-citation gap of equivalent magnitude to the one we find in JSTOR. In the SSRN data, men make up 73% of authorships but 87% of self-citations. However, the SSRN data do not support the hypotheses that this gap arises because men and women behave differently in terms of self-citation. Men with k papers in the SSRN database do not appear to self-cite appreciably more than women with k papers. However, the self-citation gap in this SSRN dataset could arise because men authors have more citation targets or because men and women who voluntarily submit papers to the SSRN are not representative of academics, more generally. The SSRN dataset differs from the JSTOR dataset on a number of important features: it is smaller, less representative, and it is a non-peer-reviewed pre-publication archive that only some authors in relevant fields elect to use, so there are many reasons to believe that selection into the database might affect results in key ways that are outside the scope of this paper to explore. However, the finding of a similar self-citation gap in a very different dataset is nonetheless reassuring to our results.

Implications

Citation follows a pattern of preferential attachment – the tendency for new citations to refer to papers that are already well-cited (Fowler and Aksnes 2007; Maliniak et al. 2013). Thus, self-citation increases the number of citations from others (Fowler and Aksnes 2007).

The gender difference in self-citation is therefore likely to be a driver of gender differences in numbers of citations received from other authors. This is not inconsequential: an academic's visibility – reflected in citation counts – has a direct, positive, and significant effect on her salary (Leahey 2007). Citation count is also a key evaluation criterion for hiring and career advancement. Given our finding that nearly 1 in 10 references in a paper is a reference to a paper written by one or more of the current paper's author(s), self-citation is an important contributor to citation counts and academic visibility. Thus, gender discrepancies in self-citation rates have notable consequences for academic careers.

The motives for self-citation vary (Hyland 2003; Safer and Tang 2009; Tang and Safer 2008), but self-citation is one of the few direct ways an academic can increase his or her own citation count. Some scholarly databases (e.g. the Thomson-Reuters Web of Science) provide a separate count of self-citations, while others (e.g., Google Scholar) do not. However, merely encouraging women to cite their own work more is not a simple solution: it may have unintended consequences due to backlash against women's self-promotion (Rudman 1998). Furthermore, insisting that scholars self-cite more in order to enhance their reputation could increase irrelevant self-citations. Should this happen, it

will become even more difficult to make accurate judgments of the quality and influence of a scholarly work.

Broadly, academic publishing provides an illustrative case for gender differences in workplace evaluation metrics. Academia is a professional realm in which the criteria for advancement are idealized to be extremely transparent: quantitative evaluation measures, such as publication counts and influence metrics, are espoused to play a substantial part in employment decisions. Understanding how these concrete evaluative systems create or reinforce gender bias provides a foundation for understanding bias in more subjective employment evaluation systems.

Investigating self-citation in particular provides a powerful case for studying self-promotion in the workplace. As a well-studied occupation, we can begin to pull apart the pieces of overall career rewards for academics that are attributable to productivity, self-promotion, recognition by others, and the recognition by others that results from self-promotion. In an occupation in which substantial gender inequity persists (Bailyn 2003; NCES 2013), the consequences of studying self-citation in academia have implications for hiring and tenure committees.

When interpreting the impact metrics of scholars' work, university hiring and tenure committees should be aware that women are likely to cite their own work less often. Considering other proposed measures for scientific impact that exclude self-citation (e.g., Ferrara and Romero 2013; West et al. 2013) could make evaluation processes less gender-biased and improve equity in the academic community.

REFERENCES

- Abramo, Giovanni, Ciriaco Andrea D'Angelo, and Gianluca Murgia. 2013. "Gender Differences in Research Collaboration." *Journal of Informetrics* 7(4):811–22.
- Aldecoa, Rodrigo, and Ignacio Marín. 2013. "Exploring the Limits of Community Detection Strategies in Complex Networks." *Scientific reports* 3:2216.
- Babcock, Linda, and Sara Laschever. 2007. *Women Don't Ask: The High Cost of Avoiding Negotiation-and Positive Strategies for Change*. New York, NY: Bantam Dell.
- Babcock, Linda, Sara Laschever, Michelle Gelfand, and Deborah Small. 2003. "Nice Girls Don't Ask." *Harvard Business Review* (October):2–5.
- Bailyn, Lotte. 2003. "Academic Careers and Gender Equity: Lessons Learned from MIT." *Gender Work and Organization* 10(2):137–53.
- Barnett, Roasalind C. et al. 1998. "Relationships of Gender and Career Motivation to Medical Faculty Members' Production of Academic Publications." *Academic Medicine* 73(2):180–86.
- Bentley, Jerome T., and Rebecca Adamson. 2004. *Gender Differences in the Careers of Academic Scientists and Engineers: A Literature Review*.
- Bozeman, Barry, and Monica Gaughan. 2011. "How Do Men and Women Differ in Research Collaborations? An Analysis of the Collaborative Motives and Strategies of Academic Researchers." *Research Policy* 40(10):1393–1402.
- Cain, Cindy L., and Erin Leahey. 2014. "Cultural Correlates of Gender Integration in Science." *Gender, Work and Organization* 21(6):516–30.

- Cech, Erin, Brian Rubineau, Susan Silbey, and Carroll Seron. 2011. "Professional Role Confidence and Gendered Persistence in Engineering." *American Sociological Review* 76(5):641–66.
- Ceci, Stephen J., Donna K. Ginther, Shulamit Kahn, and Wendy M. Williams. 2014. "Women in Academic Science: A Changing Landscape." *Psychological Science in the Public Interest* 15(3):75–141.
- Cole, Jonathan R., and Burton Singer. 1991. "A Theory of Limited Differences: Explaining the Productivity Puzzle in Science." Pp. 277–310 in *The outer circle: Women in the scientific community*.
- Correll, Shelley J. 2001. "Gender and the Career Choice Process: The Role of Biased Self-Assessments." *American Journal of Sociology* 106(6):1691–1730.
- Correll, Shelley J. 2004. "Constraints into Preferences : Gender, Status, and Emerging Career Aspirations." *American Sociological Review* 69(1):93–113.
- Ferber, Marianne A., and Michael Brün. 2011. "The Gender Gap in Citations: Does It Persist?" *Feminist Economics* 17(1):151–58.
- Ferber, Marianne A., and Michelle Teiman. 1980. "Are Women Economists at a Disadvantage in Publishing Journal Articles?" *Eastern Economic Journal* VI(3-4):189–93.
- Ferrara, Emilio, and Alfonso E. Romero. 2013. "Scientific Impact Evaluation and the Effect of Self-Citations: Mitigating the Bias by Discounting the H-Index." *Journal of the American Society for Information Science and Technology* 64(11):2332–39.
- Fowler, James H., and Dag W. Aksnes. 2007. "Does Self-Citation Pay?" *Scientometrics* 72(3):427–37.

- Fox, Mary Frank. 2001. "Women, Science, and Academia: Graduate Education and Careers." *Gender & Society* 1(5):654–66.
- Fox, Mary Frank. 2005. "Gender, Family Characteristics, and Publication Productivity among Scientists." *Social Studies of Science* 35(1):131–50.
- Handley, Ian M., Elizabeth R. Brown, Corinne A. Moss-Racusin, and Jessi L. Smith. 2015. "Quality of Evidence Revealing Subtle Gender Biases in Science Is in the Eye of the Beholder." *Proceedings of the National Academy of Sciences* 201510649.
- Heilman, Madeline E., Aaron S. Wallen, Daniella Fuchs, and Melinda M. Tamkins. 2004. "Penalties for Success: Reactions to Women Who Succeed at Male Gender-Typed Tasks." *Journal of Applied Psychology* 89(3):416–27.
- Hill, Catherine, Christianne Corbett, and Andresse St. Rose. 2010. *Why So Few? Women in Science, Technology, Engineering, and Mathematics*. Washington, DC: AAUW.
- Hunter, Laura, and Erin Leahey. 2008. "Collaborative Research in Sociology : Trends and Contributing Factors." *The American Sociologist* 39(4):290–306.
- Hutson, Scott R. 2006. "Self-Citation in Archaeology: Age, Gender, Prestige, and the Self." *Journal of Archaeological Method and Theory* 13(1):1–18.
- Hyland, Ken. 2003. "Self-Citation and Self-Reference: Credibility and Promotion in Academic Publication." *Journal of the American Society for Information Science and Technology* 54(3):251–59.
- Kanter, Rosabeth Moss. 1993. *Men and Women of the Corporation*. New York, NY: Basic Books.
- King, Edward. 1773. "A Letter to Mathew Maty, M.D. Sec. R S.; Containing Some Observations

- on a Singular Sparry Incrustation Found in Somersetshire.” *Phil Trans* 63:241–48.
- King, Edward. 1779. “Account of a Petrefaction Found on the Coast of East Lothian.” *Philosophical Transactions of the Royal Society of London* 69:35–50.
- Lancichinetti, Andrea, and Santo Fortunato. 2009. “Community Detection Algorithms: A Comparative Analysis.” *Physical Review E* 80(5):1–11.
- Larivière, Vincent, Chaoqun Ni, Yves Gingras, Blaise Cronin, and Cassidy R. Sugimoto. 2013. “Global Gender Disparities in Science.” *Nature* 504:211–13.
- Leahey, Erin. 2006. “Gender Differences in Productivity: Research Specialization as a Missing Link.” *Gender & Society* 20(6):754–80.
- Leahey, Erin. 2007. “Not by Productivity Alone: How Visibility and Specialization Contribute to Academic Earnings.” *American Sociological Review* 72(4):533–61.
- Lieberson, Stanley, Susan Dumais, and Shyon Baumann. 2000. “The Instability of Androgynous Names: The Symbolic Maintenance of Gender Boundaries.” *American Journal of Sociology* 105(5):1249–87.
- Long, J. Scott. 1992. “Measures of Sex Differences in Scientific Productivity.” *Social Forces* 71(1):159–78.
- Maliniak, Daniel, Ryan Powers, and Barbara F. Walter. 2013. *The Gender Citation Gap in International Relations*.
- McDowell, John M., and Janet Kiholm Smith. 1992. “The Effect of Gender-Sorting on Propensity to Coauthor: Implications for Academic Promotion.” *Economic Inquiry* 30:68–82.
- Merton, Robert K. 1968. “The Matthew Effect in Science.” *Science* 159(3810):56–63.

- Merton, Robert K. 1988. "The Matthew Effect in Science, II: Cumulative Advantage and the Symbolism of Intellectual Property." *ISIS* 159:606–23.
- MIT. 1999. *A Study on the Status of Women Faculty in Science at MIT*.
- MIT. 2011. *A Report on the Status of Women Faculty in the Schools of Science and Engineering at MIT, 2011*.
- Moss-Racusin, Corinne A., John F. Dovidio, Victoria L. Brescoll, Mark J. Graham, and Jo Handelsman. 2012. "Science Faculty's Subtle Gender Biases Favor Male Students." *Proceedings of the National Academy of Sciences of the United States of America*.
- Moss-Racusin, Corinne A., Julie E. Phelan, and Laurie A. Rudman. 2010. "When Men Break the Gender Rules: Status Incongruity and Backlash against Modest Men." *Psychology of Men & Masculinity* 11(2):140–51.
- NCES. 2013. *Digest of Education Statistics*.
- NSF. 2013. *Table 20. Employed Doctoral Scientists and Engineers in 4-Year Educational Institutions, by Broad Field of Doctorate, Sex, and Tenure Status: 2013*.
- NSF. 2015a. *Doctorate Recipients from U.S. Universities: 2014*. Arlington, VA.
- NSF. 2015b. *Table 14. Doctorate Recipients, by Sex and Broad Field of Study: Selected Years, 1984–2014*.
- NSF. 2015c. *Women, Minorities, and Persons with Disabilities in Science and Engineering: 2015*.
- Petersen, Alexander Michael. 2015. "Quantifying the Impact of Weak, Strong, and Super Ties in Scientific Careers." *Proceedings of the National Academy of Sciences* 112(34):E4671–80.
- Reuben, Ernesto, Paola Sapienza, and Luigi Zingales. 2014. "How Stereotypes Impair Women's

- Careers in Science.” *Proceedings of the National Academy of Sciences of the United States of America* 111(12):4403–8.
- Ridgeway, Cecilia L. 2001. “Gender, Status, and Leadership.” *Journal of Social Issues* 57(4):637–55.
- Ridgeway, Cecilia L. 2011. *Framed by Gender: How Gender Inequality Persists in the Modern World*. New York: Oxford University Press.
- Ridgeway, Cecilia L. 2014. “Why Status Matters for Inequality.” *American Sociological Review* 79(1):1–16.
- Rosvall, Martin, and Carl T. Bergstrom. 2011. “Multilevel Compression of Random Walks on Networks Reveals Hierarchical Organization in Large Integrated Systems.” *PloS one* 6(4):e18209.
- Rudman, Laurie A. 1998. “Self-Promotion as a Risk Factor for Women: The Costs and Benefits of Counterstereotypical Impression Management.” *Journal of Personality and Social Psychology* 74(3):629–45.
- Rudman, Laurie A., Corinne A. Moss-Racusin, Julie E. Phelan, and Sanne Nauts. 2012. “Status Incongruity and Backlash Effects: Defending the Gender Hierarchy Motivates Prejudice against Female Leaders.” *Journal of Experimental Social Psychology* 48(1):165–79.
- Safer, Martin A., and Rong Tang. 2009. “The Psychology of Referencing in Psychology Journal Articles.” *Perspectives on Psychological Science* 4(1):51–53.
- Schiebinger, Londa, and Shannon K. Gilmartin. 2010. “Housework Is an Academic Issue: How to Keep Talented Women Scientists in the Lab, Where They Belong.” *Academe*.
- Smalheiser, Neil R., and Vetle I. Torvik. 2009. “Author Name Disambiguation.” *Annual Review*

of Information Science and Technology 43(1):1–43.

Snyder, Herbert, and Susan Bonzi. 1998. “Patterns of Self-Citation across Disciplines (1980-1989).” *Journal of Information Science* 24(6):431–35.

Šubelj, Lovro, Nees Jan van Eck, and Ludo Waltman. 2015. “Clustering Scientific Publications Based on Citation Relations: A Systematic Comparison of Different Methods.” 1–24.

Symonds, Matthew R. E. E., Neil J. Gemmell, Tamsin L. Braisher, Kylie L. Gorringer, and Mark A. Elgar. 2006. “Gender Differences in Publication Output: Towards an Unbiased Metric of Research Performance.” *PLoS ONE* 1(1):e127.

Tang, Rong, and Martin A. Safer. 2008. “Author-Rated Importance of Cited References in Biology and Psychology Publications.” *Journal of Documentation* 64(2):246–72.

Thébaud, Sarah. 2010. “Gender and Entrepreneurship as a Career Choice: Do Self-Assessments of Ability Matter?” *Social Psychology Quarterly* 73(3):288–304.

Weisshaar, Kate. n.d. “Publish and Perish?: An Assessment of Gender Bias in Academia.” *Working paper*.

Wesley-Smith, Ian, Carl T. Bergstrom, and Jevin D. West. 2016. “Static Ranking of Scholarly Papers Using Article-Level Eigenfactor (ALEF).” in *WSDM Conference: Entity Ranking Challenge Workshop*.

West, Jevin D., Jennifer Jacquet, Molly M. King, Shelley J. Correll, and Carl T. Bergstrom. 2013. “The Role of Gender in Scholarly Authorship.” *PloS one* 8(7):e66212.

West, Jevin D., Michael C. Jensen, Ralph J. Dandrea, Gregory J. Gordon, and Carl T. Bergstrom. 2013. “Author-Level Eigenfactor Metrics: Evaluating the Influence of Authors, Institutions, and Countries within the Social Science Research Network Community.” *Journal of the*

American Society for Information Science and Technology 64(4):787–801.

West, Jevin D., Martin Rosvall, and Carl T. Bergstrom. 2016. “Ranking and Mapping Article-Level Citation Networks.” *In prep.*

Xie, Yu, and Kimberlee A. Shauman. 1998. “Sex Differences in Research Productivity: New Evidence About an Old Puzzle.” *American Sociological Review* 63(6):847–70.