Publish *and* Perish?

Publish *and* Perish? An Assessment of Gender Gaps in Promotion to Tenure in Academia

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In academia, there remains a gender gap in promotion to tenure, such that men are more likely to receive tenure than women. This paper tests three explanations of this gender gap in promotion: (1) contextual and organizational differences across departments; (2) performance/productivity differences by gender; and (3) gendered inequality in evaluation. To test these explanations, this project uses a novel dataset drawing from a sample of assistant professors in Sociology, Computer Science, and English, across research universities. This dataset combines data from sources including curriculum vitae, Google Scholar, and web archive employment data, resulting in a dataset of assistant professors' publication records, department affiliations, and job positions. Analyses examine the gender gap in the likelihood of promotion to tenure and in early career trajectories, while accounting for publication productivity and department/university context. The results demonstrate that productivity measures account for a portion of the gender gap in tenure, but in each discipline a substantial share of the gender gap remains unexplained by these factors. Department characteristics do not explain the tenure gender gap. Further, when women do receive tenure, they do so in lower-prestige departments than men, on average. These findings suggest that gendered inequality in the tenure evaluation process contributes to the gender gap in tenure rates.

Introduction

Gender gaps in promotion rates have persisted in recent years, despite the widespread belief in meritocracy and the push for workplace evaluations to be made solely based on performance—rather than on ascribed characteristics such as gender (McNamee and Miller 2009). Put simply, women in the workplace are less likely to receive promotions than men. This discrepancy in promotion rates has led to fewer women attaining high-status positions within organizations across many occupational domains. Compared to men, women are less likely to hold managerial positions (Cotter et al. 2001); serve on executive boards (Ragins, Townsend, and Mattis 1998); become partners in law firms (e.g., Gorman and Kmec 2009);

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and in academic contexts, women are less likely than men to receive tenure and full professorships (Booth, Francesconi, and Frank 2003; Fox 2005; Ginther and Hayes 1999). Scholarship suggests that gendered processes continue to interfere with the assessment of women's work and likelihood of career advancement, even as overt gender attitudes have liberalized (e.g., Castilla 2008; Cotter, Hermsen, and Vanneman 2011; McNamee and Miller 2009).

What accounts for gender differences in promotion rates? Theories point to several potential factors: (1) sex segregation across types of workplaces; (2) gender differences in job performance leading up to the promotion decision; and (3) gendered processes and inequality at the time of promotion decisions. Sex segregation may lead to aggregate-level gender gaps if women disproportionately work in organizational contexts with worse promotion opportunities. Gender differences in job performance may contribute to the gender gap in promotion if women are less likely to meet promotion standards. Finally, gender inequality at the time of the promotion could be a culprit, as would be suggested if men and women with equivalent qualifications in similar organizations are promoted at different rates. It is important to establish which of these reasons are at play, and to what extent each reason contributes to gender gaps in promotion, in order to develop precise solutions to address this type of inequality.

To test the explanations behind the gender gap in promotion rates, this paper examines one form of promotion: promotion to tenure at research universities in academia. In many occupations, both productivity and organizational context are difficult to measure. To measure productivity, scholars must rely on proxies, such as hours worked or self-rated productivity, which can be imprecise or contain gender bias in reporting (Jacobs 1998). Studying the role of organizational context requires both sufficient variation and comparable promotion processes across workplaces. Academia is a domain that satisfies measurement requirements on each of these factors: research output and publications are largely accepted as being representative of a scholar's productivity (e.g., Long, Allison, and McGinnis 1993), and the process of promotion to tenure is relatively invariant across different schools and disciplines.

While prior scholars of academia have examined each theoretical explanation behind the gender gap in tenure separately, there has not been a simultaneous test to determine the relative influence of each process. To do so requires detailed data on men's and women's employment history, productivity, and data on department and university contexts. To fulfill these data requirements, I have created a unique longitudinal dataset of employment history coded from the curricula vitae of a stratified random sample of academics who were assistant professors in three disciplines: Sociology, Computer Science, and English. Combining data of professors' academic positions and career histories with their complete publication records and measures of their departmental affiliations, I predict promotion to tenure after accounting for highly detailed measures of research outputs and organizational composition in departments and schools. Because it is possible for multiple explanations to occur simultaneously, I conduct a decomposition analysis to assess the relative influence of productivity and context on the gender gap in receiving tenure. Finally, I analyze where these professors received tenure, and examine the extent to which men and women are tenured in departments that vary by prestige ratings.

I find that productivity differences by gender account for a portion—but not all—of the gender gap in tenure rates, but sex segregation across departments does not explain the gender gap in tenure. In all three academic disciplines, women remain disadvantaged in receiving tenure even after accounting for productivity and contextual differences. Further, when women receive tenure, they do so in lower-prestige departments than men, on average. These findings suggest that gendered processes during promotional decisions contribute to women's lower likelihood of receiving tenure.

Theoretical Models for Gender Inequality in Promotion Attainment

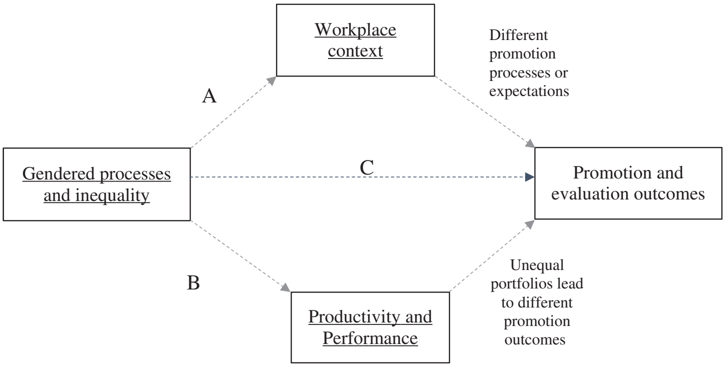
Theoretical explanations for women's lower promotion rates—drawn from studies both in academia and in other occupational settings—suggest that gendered processes produce inequality in promotion through factors that occur both prior to and during the promotion evaluation. These explanations yield the theoretical model depicted in figure 1.

An overall gender gap in promotion rates is the aggregate of many promotion decision outcomes. These decisions can be decomposed into several processes, which allows one to examine in which stages gender inequality occurs. Promotion decisions occur within organizational contexts, which themselves may be gendered due to sex segregation across workplaces. If gendered processes lead to different *placement* into workplaces, then workplace contexts can in turn affect the gender gap in promotion. Additionally, the promotion decision is an evaluation based on work quality, productivity, and job performance, which are accumulated over time, during the *production stage*. Gender inequality could affect performance, such that in the aggregate, men and women have unequal portfolios at the time of promotion decisions. Net of sex segregation and performance, decisions about promotion during the *evaluation stage* (from both the employer and employee) can themselves be gendered. In this section, I describe each explanation, and highlight relevant scholarship within each theoretical domain.

Organizational Context of Workplaces Produces Gendered Patterns

Gendered processes during the *placement stage*—the period during which individuals place into jobs—can lead to gender compositional differences across workplaces, which may create unequal promotion opportunities for men and women. Labor market scholars have identified that sex segregation can occur across occupations and within an occupation, across firms and positions (Charles and Grusky 2004). Horizontal sex segregation refers to men and women's uneven distribution across types of occupations; in the academic context, men and women are unevenly distributed into academic disciplines, with women being underrepresented in science and math disciplines, and overrepresented in some humanities fields (Cech 2013; Charles and Grusky 2004; Reskin and Roos

Figure 1. Theoretical diagram and examples of gendered processes influencing promotion outcomes



A: *Gendered processes in placement*. Examples include:

- Sex segregation (vertical and horizontal), caused by:
  - o Constrained choices in job location
  - o Biases at time of hire
  - o Self-assessment of career goals and preferences
- Gender differences in workplace context (size of department, promotion criteria/processes)

B: *Gendered processes in production.* Examples include:

- Mentoring and facilitation of projects
- Types of projects and impact (differences from bias or self-assessments)Family and household responsibilities interfere with productivity

C: *Gendered processes in evaluation*. Examples include:

- Women's work devalued or scrutinized by colleagues
- Explicit gender biases
- Women's self-selection out of promotion review
- Strength of networks, types of recommendations

1990). Vertical sex segregation in the labor market refers to men's overrepresentation in high-status roles within a particular occupation (Charles and Grusky 2004; Jacobs 1989; Reskin and Roos 1990). In academia, vertical segregation occurs in terms of both department prestige and positions within departments. If women are concentrated in lower-prestige departments and schools, they have lower access to resources and connections at high-status institutions. The "leaky academic pipeline" refers to vertical segregation of positions: women are less likely to be in tenure-track positions than men, less likely to receive tenure, and less likely to receive full professorships (Misra, Kennelly, and Karides 1999; Probert 2005).

Men and women could also be unevenly distributed across types of departments and schools in other ways. The type of university (public or private), the department's size, and the department's composition by faculty rank are factors that could produce variation in promotion rates across departments and schools. If women are concentrated in departments where it is more difficult to receive tenure, then an observed gender gap in tenure could be in part due to the department context.

Gender inequality in terms of initial job choice, biases in hiring, or women's self-assessments in terms of career goals, interests, and preferences can all cause this type of sorting across fields and departments (Cech 2013; Charles and Grusky 2004; Correll 2004; Misra, Kennelly, and Karides 1999; Reskin and Roos 1990). In other words, both supply- and demand-side processes can contribute to sex segregation. Importantly, sex segregation across disciplines, departments, and workplace context occurs prior to the tenure decision, but this placement stage can have lasting consequences on an individual's career trajectory.

Gender and Productivity

Neoclassical economic theories of human capital and theories of meritocracy within organizations propose that workplace rewards, including to promotion, are (or ought to be) distributed according to job performance (see Becker 1985; Bielby and Baron 1986; McNamee and Miller 2009). According to such theories, women's lower rates of promotion could be attributable to *gendered processes in production* (Long 1978; Xie and Shauman 2003). If women were found to have lower productivity outputs, this is not due to gender differences in talent or competence; instead, factors such as mentoring, service loads, and gendered divisions of labor in the household can lead to gendered differences in opportunities and preferences, which in turn can affect performance (West et al. 2013). Nonetheless, gender differences in production prior to the promotion decision may result in women receiving weaker evaluations and, in turn, lower promotion rates.

Sociological research on academia finds that women academics have different time use patterns than their male counterparts (Misra, Lundquist, and Templer 2012). Women are more likely to serve on university and department committees, dedicate more time to teaching and mentoring students, and mothers tend to have more family obligations than fathers, such as childcare and housework (Mason, Wolfinger, and Goulden 2013; Misra, Lundquist, and Templer 2012; Winslow 2010). Since research production is the primary determinant of tenure chances at research universities, obligations that compete for research time can reduce professors' research outputs (Long, Allison, and McGinnis 1993; Misra, Lundquist, and Templer 2012; Pyke 2014).

Gendered processes could also reduce women's opportunities for collaborative projects, grants, and media attention. Erin Leahey suggests that specialization is one cause of gender differences in research productivity among academics: men are more likely than women to specialize in a subfield, which yields an advantage in publication rates (2006, 2007). Inequality could also affect women's self-evaluations, which has the potential to change their research-based decisions (e.g., submitting to the best journals or applying for large grants). For example, recent studies demonstrate that women are less likely to self-cite their own research than are men, even net of the quantity of research produced (King et al. 2016). Such findings further emphasize that productivity is not a proxy for talent or intelligence; nevertheless, it is still used to measure performance and serves as a basis to assign rewards such as promotion and salary.

Gender Inequality in Evaluations

Finally, *gendered processes in evaluation* can influence promotion rates. This can be conceptualized as the "remaining" gender gap that is not explained by productivity differences or contextual workplace differences. This type of inequality comes from several factors, including evaluators not giving the same recognition to women as to men for equal work quality; women self-selecting into different career paths before promotion review takes place; or inequality in networks and advocacy of a promotion candidate (e.g., Misra, Lundquist, and Templer 2012).

While it is possible that some portion of gender inequality in evaluation arises from gender discrimination—a taste-based preference for men over women in a comparison of otherwise equivalent individuals (Bielby and Baron 1986)—social psychological research suggests that these processes occur on a more subtle and unconscious level (Ridgeway 2011). For example, gender expectations lead to women's accomplishments being overly scrutinized relative to men with the same record (Castilla 2008; McNamee and Miller 2009). In letters of recommendation for faculty positions, studies have found that women are more likely to be praised for their "communal" skills (i.e., collaboration), whereas men received more mentions of "agency": being "brilliant" at research or a "genius" (Madera, Hebl, and Martin 2009). Subtle gender expectations affect the way that work accomplishments are perceived. Consider a coauthored paper with a senior faculty member: if the author is a woman, her contribution to this paper might be scrutinized more than if the individual is a man (Madera, Hebl, and Martin 2009). Additionally, if women tend to put more time toward university service and mentorship than men (Misra, Lundquist, and Templer 2012; Pyke 2014), even if they have productive research portfolios they could face penalties for not prioritizing research.

Another way that gender could influence evaluations is when mothers are the subject of evaluation. "Stop the tenure clock" policies are meant to assist junior faculty who have children during the pre-tenure years, and typically allow faculty members to add time to the tenure clock after having children (Mason, Wolfinger, and Goulden 2013). Stopping the clock is not intended to harm tenure chances, but scholars have suggested that these policies might exacerbate gender inequality, since evaluators have difficulty adjusting productivity expectations for the stopped tenure clock (Lundquist, Misra, and O'Meara 2012; Manchester, Leslie, and Kramer 2010). Moreover, some mothers report the expectation of proof that they can continue to be productive after having children, an expectation that is less commonly placed on fathers (Mason, Wolfinger, and Goulden 2013). Family formation patterns could also unevenly lead to career decisions for women and men—if there are gender differences in the likelihood of moving or changing jobs to accommodate family or partners, these (constrained) choices can affect career outcomes (e.g., Mason, Wolfinger, and Goulden 2013).

In these ways and more, gender can color our evaluation of others in ways that are often imperceptible. While usually unmotivated by overt gender bias, these subtle processes can accumulate to have substantial effects on career outcomes.

What Does Existing Data Tell us About Promotion to Tenure?

Two surveys have contributed to a substantial body of scholarship on academic career trajectories: the Survey of Doctorate Recipients (e.g., Ginther and Hayes 1999), and the National Study of Postsecondary Faculty (e.g., Perna 2005). These surveys ask questions about career progression, and in some years, the surveys ask faculty to self-report their number of publications, a measure of productivity. Using these surveys, scholars have found that women are less likely to be promoted with tenure, even after controlling for number of publications (e.g., Ginther and Hayes 1999). Several studies have found that the gender gaps in productivity and promotion are concentrated among mothers, but others debate this finding (see Perna 2005; Sax et al. 2002; Stack 2004).

The studies that have used existing survey data are informative and lend evidence for each of the theories highlighted above. However, data limitations have not allowed for a precise test of these explanations simultaneously. Self-reported number of publications is an important performance measure (e.g., Long 1978; Sax et al. 2002; Stack 2004), but the measures in existing surveys may provide an incomplete picture of research productivity. For one, the number of publications is not the sole indicator of research productivity (see Leahey 2007). Additionally, women and men may vary in what kinds of research output they count as "publications" in such surveys (see King et al. 2016). Further, it is plausible that nonresponses to these surveys are correlated with negative career outcomes. Some scholars have developed innovative data collection strategies to measure productivity based on CVs, bibliographic databases, or university databases (e.g., Leahey 2007; Long and McGinnis 1981; Long, Allison, and McGinnis 1993; Xie and Shauman 2003), but even these strategies could miss individuals who do not have CVs, have not published in a bibliographic database, or change universities. In short, developing more precise data on productivity, career trajectories, and department context is a worthwhile endeavor to be able to simultaneously test mechanisms producing the gender gap in tenure.

Data and Methods

This study employs an original dataset that combines data from department websites, assistant professors' CVs, Google Scholar records, and National Research Council (NRC) measurements of department and school characteristics. First, I used data from the NRC's 1995 list of research universities with departments in three disciplines: Sociology, English, and Computer Science. I selected these disciplines to achieve range in levels of gender composition and to cover diverse subject matter. According to the 2006 NRC report, 13 percent of faculty members in Computer Science were female, 39 percent of Sociology faculty members were female, and 46 percent of English faculty members were female (NRC 2010). The 1995 NRC data also includes a prestige ranking of departments. The NRC ranked 95 Sociology departments, 127 departments in English, and 108 Computer Science departments. Using Internet archival data,[1] I visited the websites of each of these departments dating from 2000 to 2004 and recorded the names of assistant professors listed during that time period.

I then drew a random sample of 475 assistant professors in Sociology, 606 in Computer Science,[2] and 478 in English, oversampling professors from departments that were ranked in the top 30 by the 1995 NCR data to increase accuracy in assessing women's access to the highest-prestige departments. With this strategy, I collected a stratified random sample of faculty members who were assistant professors in at least one year from 2000 to 2004 within each field.[3] I then conducted Internet searches for each professor. When possible, I downloaded his/her CV to obtain employment history. For individuals with no available CV, I gathered missing information using several methods. For the majority of these professors, I was able to track their career progress with web archive data, examining yearly snapshots of their personal website or department websites from the time they began as an assistant professor to the time their title or position changed to indicate tenure receipt. For professors who had neither an online CV nor sufficient web archive data, I e-mailed a survey in the spring of 2014, asking for a CV or employment history.[4] I hand-coded the CV, web archive, and survey information for each individual to generate an event history dataset, with year-by-year data on changes in institution and faculty positions held. I then used a Python script and web scraping techniques to collect each professor's publication record from Google Scholar, and added this data to the event history dataset. Finally, I merged NRC data on department context to examine variation across types of departments.

This multifaceted data collection strategy yielded complete employment data on a substantial proportion of the professors in the initial sample: 88.2 percent of Sociology professors, 73.2 percent of English professors, and 89.7 percent of Computer Science professors. For the remaining individuals, I have partial information that can be used to impute missing data (see appendix table A1).[5] Using this dataset, I am able to predict promotion to tenure, while accounting for publication productivity and department context.

Independent Variables

The subsequent analyses use the same sets of independent variables, to assess the roles of gender differences in productivity, department context, and gendered processes in evaluation on tenure outcomes.

Productivity Measures

Publication data were scraped from Google Scholar using a Python script. The process for gathering the information was as follows: first, I searched for each professor on Google Scholar (e.g., author: "Shelley Correll"). This returns all Google Scholar results that have an author matching the search term. Next, I downloaded the citation data for each search result. The citation gives the publication type (e.g., article, book, conference paper), along with the authors, title, journal name, year of publication, and citation count.[6] In addition to publications, I also searched for NSF grant awards for each author in Sociology and Computer Science, to account for another dimension of productivity.

Using these data, I created multiple variables to measure both the quantity and quality of research productivity. I measure quantity as the cumulative count of the number of journal articles, books by type (research monographs, textbooks, and edited volumes), book chapters, and (for Computer Science) conference presentations. In the event history models (described below), the measures are cumulatively summed over duration as an assistant professor. For instance, if a professor published his/her first article in 2000 and the second in 2002, the count for journal articles would be 0 prior to 2000, 1 in 2000, 1 in 2001, and 2 in 2002. For faculty in Sociology and Computer Science, disciplines in which major grant funding may count toward tenure decisions, I include variables counting the number of NSF grants and dollar amount of NSF grants.

I measure the quality/visibility of research productivity with three measures. I include a binary variable that is coded as 1 if the professor has published in the highest-prestige journals in their discipline. For Sociology, this is composed of the *American Journal of Sociology*, *American Sociological Review*, and *Social Forces*. For Computer Science and English departments, these include the top five journals determined by impact factor. I also include a variable that reflects the cumulative percentage of first-authored[7] and single-authored publications, as departments tend to favor these types of publications in tenure decision processes. I measure publication visibility with the average citation count per year since the publication date, per publication.

I measure each of the above productivity variables at three time periods: 1) the five years prior to beginning an assistant professorship, when faculty members would be publishing as graduate students or postdoctoral fellows; 2) the years an individual served as an assistant professor—the primary time period to acquire publications toward the tenure decision; and 3) the year after a tenure decision is made, since these publications were likely included as part of a professor's tenure review and could have been accepted or had a revise-and-resubmit status before the tenure decision.

Department and School Contextual Measures

I use measures from the NRC's 1995 and 2006 datasets on research universities to include independent variables on department and institutional context. These measures serve to test the theory that gender composition across types of workplaces is contributing to inequality in tenure rates. First, I include a measure of the percent of female faculty members in the department at the time of the NRC survey. I also include measures of department size (the total number of faculty) and composition of faculty (the percent of full professors in the department) because size and composition could influence internal tenure promotion rates. Next, I measure whether the university is public or private, because of possible variation across universities in tenure rates. I control for the 1995 NRC prestige ranking[8] of the department, since it tends to be more challenging to receive tenure at higher-ranked departments. In this continuous measure, a higher number indicates higher prestige, and the lowest ranking (1) is for the lowest-ranked department from the NRC data.

Variation Across Career Timing and Moves

Finally, two career trajectory measures are included in all models. I control for whether the individual moved schools as an assistant professor, or remained at one school, since moving could change tenure timing. Further, I control for duration as an assistant professor. Duration is an important control for two reasons. First, if tenure timelines are paused or extended (i.e., for having children or moving), then these timing changes could affect tenure likelihood. Insofar as these are gendered processes, tenure timing delays could contribute to the gender tenure gap (Manchester, Leslie, and Kramer 2010). Second, it is possible that men are more likely than women to receive early tenure (Booth, Francesconi, and Frank 2003). This can occur if a professor has an outside job offer of a tenured position, which might then induce an early tenure decision.

Gendered Processes in Evaluation

I measure gender inequality in evaluation as the gap in outcomes between men and women[9] that remains after inclusion of indicators of productivity and department context. Given this approach to measuring inequality, it is important to consider the possibility that there exist omitted variables such that, if these measures were included in the models, the gender gap in tenure would be further reduced. I argue that the remaining gender gap could be composed partially of gender bias, but also likely consists of other gendered processes that disadvantage women. These other processes are not clearly rooted in bias, but are a result of the gendered arrangement of our work and family systems. For example, these gendered processes could include a devaluation of women's work, gender differences in recommendations and networks, perceptions of fit in the department, or could be in part due to gender inequality in career decisions—for example, women might select out of promotion reviews by leaving academia (Fox 2005). In the Discussion section, I speculate both on possible omitted variables that could further reduce the gender gap, and on the processes encompassed in the remaining gender gap. For now, I label the remaining gender gap as gendered processes in evaluation, while recognizing that it is an imperfect measure and consists of multiple gendered mechanisms.

Methods and Outcome Variables

Rather than simply studying whether tenure was received or not, I argue that it also matters when and where tenure was received. The majority of assistant professors who do not receive tenure at one department do not leave academia; instead, they move to a different institution and either receive tenure upon arrival or spend additional time as an assistant professor. Furthermore, assistant professors frequently move schools before the tenure decision arises. These moves could be for family reasons, location preferences, better job fit, or improved resources. These different career paths could themselves be gendered. For example, women may be more likely to leave academia or to move to less prestigious departments before attaining tenure, while men may be more likely to achieve tenure in their original departments or more prestigious departments.

I therefore examine the outcome of gender gaps in promotion to tenure in three analyses. The first analysis consists of a discrete time event history analysis, predicting receipt of tenure. This analysis assesses whether women are less likely to obtain tenure, after accounting for productivity, department and school characteristics, and career timing measures. The dependent variable is 0 if the individual did not receive tenure in a given year and 1 if tenure was received. Next, a decomposition analysis of the gender gap in tenure serves to examine the multiple theoretical explanations for gender differences in promotion. In this analysis, I use logistic regressions and Fairlie decomposition techniques to decompose the gender gap in tenure rates for both 1) the original department in which an individual began as an assistant professor; and 2) overall, at any type of department. The final analysis compares the prestige ranking of the starting institution to the rank of the tenure-granting department. The dependent variable is the prestige rank of the tenure department, and this analysis employs Tobit models to address censored individuals who received tenure in a non-ranked department. Here we can determine if gender matters when professors move to higher- or lower-prestige departments when they receive tenure. This analysis additionally tests whether vertical sex segregation of department prestige is taking place at the tenure stage.

Results

Descriptive Findings

Table 1 gives the descriptive statistics for each discipline. Across all disciplines, on average women take longer than men to receive tenure, and are less likely to receive tenure. For instance, in Sociology, approximately 78.1 percent of women receive tenure, compared to about 85.4 percent of men. Note that this is the likelihood of receiving tenure *at all* in the observation window, and tenure could be received in any department. In Computer Science, about 86.4 percent of men in the sample received tenure, compared to 80.8 percent of women. Among English faculty in the sample, 85.9 percent of men received tenure, as did 79.7 percent of women. Relative to the overall tenure rates, there is a larger gender gap in English and Sociology departments when examining faculty who received tenure in their original department (in which they began their assistant professor careers): for example, in Sociology, 49.1 percent of women receive tenure in their original departments, compared to 58.2 percent of men.

There are several significant differences between men and women on productivity measures, which vary by discipline. For example, in Sociology, women publish fewer articles in "top" journals. In both Sociology and Computer Science, women publish fewer journal articles overall, and receive fewer citations per publication

Table 1. Descriptive Statistics for Men and Women Assistant Professors in Each Discipline

	Sociology			Computer Science			English		
	Men	Sig.	Women	Men	Sig.	Women	Men	Sig.	Women
Dependent variables									
Received tenure at any school	0.854	**	0.781	0.864	*	0.808	0.859	+	0.797
Received tenure at original school	0.582	**	0.491	0.505	*	0.458	0.717	**	0.599
Time to tenure	6.599 [1.727]	***	7.207 (2.303)	6.443 (2.375)	*	6.942 (2.391)	6.8 56 (1.679)	***	7.679 (2.088)
Department rank at tenure (higher is more prestigious)	58.169 (26.297)	*	53.489 (26.245)	70.784 (30.336)	*	62.305 (32.282)	85.782 (35.318)	+	82.174 (35.616)
Productivity variables									
Has a top journal article (=1)	0.535	***	0.388	0.124	n.s.	0.092	0.038	*	0.082
Number of other journal articles	6.042 (4.971)	+	5.488 (4.195)	7.357 (8.405)	**	6.046 (6.300)	2.268 (2.628)	n.s.	2.161 (2.500)
Number of research books	0.414 (0.691)	n.s.	0.365 (0.584)	0.119 (0.419)	n.s.	0.110 (0.410)	0.799 (0.924)	n.s.	0.832 (1.097)
Number of edited volumes	0.019 (0.166)	n.s.	0.019 (0.138)	0.019 (0.152)	n.s.	0.006 (0.076)	0.072 (0.277)	n.s.	0.037 (0.199)
Number of textbooks	0.005 (0.068)	n.s.	0.012 (0.107)	0.002 (0.048)	n.s.	0.006 (0.076)	0.000 –		0.000 –
Number of book chapters	0.553 (1.039)	n.s.	0.492 (0.836)	0.619 (1.342)	n.s.	0.480 (0.974)	0.120 (0.380)	n.s.	0.086 (0.352)
Number of conference publications	–		–	23.836 (18.885)	n.s.	22.642 (19.778)	–		–

% First-/single-authored publications†	70.717	n.s.	68.857	18.794	*	15.703	71.686	n.s.	75.430
	(26.483)		(28.901)	(15.170)		(14.344)	(41.280)		(38.324)
Average citations per publication	3.363	+	2.865	4.475	***	3.234	0.809	n.s.	0.769
	(4.745)		(2.691)	(5.115)		(3.381)	(1.618)		(1.182)
Number of NSF grants	0.167	n.s.	0.138	1.206	n.s.	1.052	–		–
	(0.493)		(0.398)	(1.600)		(1.464)			
Dollar amount of NSF grants	$26886	+	$14725	$351334	*	$264677	–		–
	(95077)		(61543)	(487983)		(383019)			
Dept. & school variables									
Stayed at one school (yes = 1)	0.711	n.s.	0.688	0.685	n.s.	0.653	0.850	*	0.817
NRC department ranking (higher is more prestigious)	62.671	n.s.	60.828	72.977	n.s.	73.289	92.429	n.s.	91.807
	(20.987)		(21.602)	(27.508)		(27.172)	(31.296)		(30.434)
Department faculty size	33.454	n.s.	32.952	57.744	n.s.	60.942	52.476	+	55.833
	(11.249)		(11.848)	(36.060)		(41.166)	(22.978)		(22.547)
% Full faculty in department	73.355	n.s.	72.489	65.647	n.s.	66.405	76.592	n.s.	77.484
	(11.177)		(12.979)	(12.641)		(11.877)	(9.594)		(9.127)
% Female faculty in department	40.033	n.s.	40.081	12.756	***	14.488	44.925	*	46.661
	(7.969)		(9.743)	(5.215)		(5.908)	(7.683)		(7.600)
Public university (= 1)	0.711	n.s.	0.699	0.594	+	0.570	0.599	*	0.726
Total *N* (%)	216		260	432		174	209		269
	(45.47%)		(54.53%)	(71.29%)		(28.71%)	(43.72%)		(56.28%)

Note: Statistics are unweighted; standard deviations are in parentheses.
+ $p < 0.10$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$.
"Sig." column refers to whether there are significant differences between men and women within a discipline. Sample consists of an oversample of top 30 departments and women (see appendix for sampling details). Subsequent analyses are weighted to account for sampling process.
†In Computer Science, last author is generally considered the most prestigious position on a coauthored publication, and this measure is adjusted so that it represents the % of last- or single-authored publications.

than men, on average. In Computer Science, women are less likely to hold the last author position or publish as a single author than are men. Among English faculty, the only significant productivity difference is the likelihood of publishing in a "top" journal, and women outperform men on this measure.

In terms of department context variables, the data show that women and men tend to be in somewhat different types of departments. Men tend to receive tenure in higher-ranked departments than women assistant professors, and in Computer Science and English departments women assistant professors are in departments with higher percentages of female faculty members, on average. Women computer science faculty are somewhat less likely to be in public universities than men, whereas women in English departments are more likely than men to be in public universities.

Likelihood and Duration to Tenure

Models and methods

The first analysis examines whether there are gender differences in receiving tenure after accounting for productivity, department context, and career timing measures. I use a person-year dataset and a discrete time event history model to assess this question. The dependent variable is binary ($Y = 0$ or 1), and observation receives a 1 for this variable for the year in which they received promotion to tenure, and a 0 otherwise. The variables discussed above will be included in the following model:

$$log\left(\frac{P_{it}}{1 - P_{it}}\right) = \alpha_t + X_{it}\beta.$$

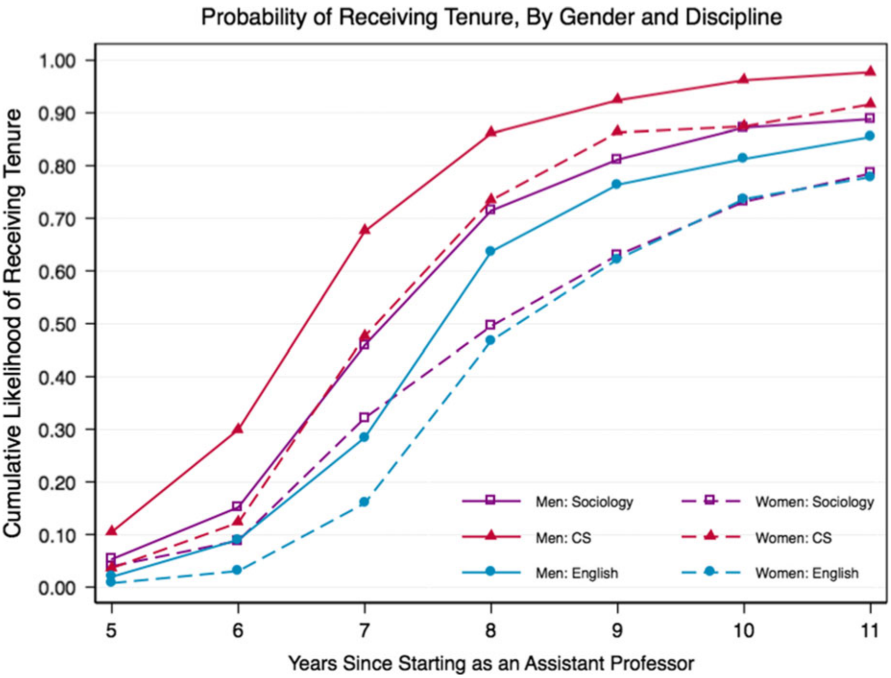
This equation is interpreted as we would interpret a logit regression: it estimates the log-odds of experiencing an event compared to not experiencing the event, for a particular assistant professor at time t. In the above equation, α_t is the baseline hazard rate (assumed to be constant in discrete time models), X_{it} represents a vector of independent variables (both time varying and not), and β_i is a vector of parameter estimates.

Results

Figure 2 shows the cumulative hazard plot over duration as an assistant professor, predicting the cumulative likelihood of receiving tenure by gender and discipline. Across all fields, a gender gap exists in the likelihood of receiving tenure: male assistant professors are more likely than their female counterparts to receive tenure in a given year. Since a gender gap does exist in the data, the next question is whether we can account for this difference by accounting for productivity measures and department context.

In table 2, coefficients at the log-rate level are presented from discrete time event history models. Results from each discipline are shown in the same table, but analyses are run separately by discipline. Model 1 gives the baseline effect of gender on likelihood of receiving tenure in a given year, controlling for duration as an

Figure 2. Cumulative hazard plot of receiving tenure, by gender and field, over career time. "Years since starting" indicates the number of years spent as an assistant professor.



assistant professor, and duration-squared.[10] Model 2 controls for measures of publication productivity. Model 3 adds characteristics of the department and school, which are time varying to account for professors moving to different schools.

Table 2 shows that women's lower chance of receiving tenure is statistically significant across all disciplines, even with the inclusion of productivity and department factors. Model 3 estimates that in Sociology departments, women's odds of receiving tenure in a particular year are about 29 percent lower than men's ($=1-\exp(-0.345)$), even if they are equally productive on the included productivity measures and work in the same type of departments. The estimated gender gap in receiving tenure among Computer Science assistant faculty is also persistent: women's odds of receiving tenure in a certain year are lower than men's by a factor of 45.7 percent ($=1-\exp(-0.611)$), after accounting for publication productivity and department context measures. In model 3, English women faculty are estimated to have lower odds of receiving tenure relative to men by about 37.4 percent ($=1-\exp(-0.472)$) in a particular year.

Several productivity variables are significant predictors of receiving tenure. For example, among Sociology faculty, publishing in a top journal, the number of journal articles, the number of research books published, and the number of edited volumes are all strong positive and significant factors in receiving tenure. In Computer Science, the number of textbooks published and the percent of single- or last-authored publications are positive predictors of receiving tenure, and

Table 2. Discrete Time Event History Models Predicting Promotion to Tenure, for Sociology, Computer Science, and English Assistant Professors

	Sociology			Computer Science			English		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Independent variables									
Gender (female = 1)	−0.514*** (0.128)	−0.359* (0.141)	−0.345* (0.144)	−0.622*** (0.119)	−0.527*** (0.157)	−0.611*** (0.170)	−0.597*** (0.145)	−0.480** (0.153)	−0.472** (0.157)
Duration as assistant prof.	2.106*** (0.182)	1.974*** (0.206)	2.038*** (0.208)	3.534*** (0.310)	2.909*** (0.314)	2.989*** (0.321)	2.040*** (0.245)	1.844*** (0.296)	1.875*** (0.294)
Duration^2	−0.104*** (0.011)	−0.097*** (0.012)	−0.095*** (0.012)	−0.204*** (0.022)	−0.159*** (0.022)	−0.163*** (0.022)	−0.094*** (0.014)	−0.086*** (0.017)	−0.086*** (0.017)
Productivity Measures									
Has top journal article (yes = 1)		0.279+ (0.145)	0.506** (0.155)		0.176 (0.331)	0.209 (0.308)		0.305 (0.393)	0.366 (0.402)
Number of other journal articles		0.204*** (0.023)	0.207*** (0.021)		−0.006 (0.012)	−0.010 (0.012)		0.161*** (0.044)	0.174*** (0.042)
Number of books									
Number of research monographs		0.593*** (0.121)	0.619*** (0.126)		0.227 (0.183)	0.271 (0.187)		0.504*** (0.134)	0.471*** (0.137)
Number of edited volumes		0.628+ (0.343)	0.622* (0.307)		0.311 (0.389)	0.002 (0.486)		0.816** (0.264)	0.801** (0.275)
Number of textbooks		0.256 (0.841)	0.074 (0.748)		2.234*** (0.626)	2.268** (0.724)		–	–
Number of book chapters		−0.035 (0.077)	−0.007 (0.075)		−0.152* (0.069)	−0.160* (0.072)		−0.074 (0.200)	−0.124 (0.204)
Num. of conference presentations		–	–		−0.029 (0.025)	−0.022 (0.026)		–	–
% First-/single-authored publications		−0.003 (0.002)	−0.001 (0.003)		0.105*** (0.011)	0.112*** (0.011)		0.003 (0.002)	0.003 (0.002)

Average citations per publication		−0.011	0.001		−0.006	−0.002		0.067**	0.063*
		(0.013)	(0.010)		(0.005)	(0.005)		(0.025)	(0.028)
Number of NSF grants		0.236	0.346		−0.149*	−0.131+		–	–
		(0.209)	(0.237)		(0.071)	(0.074)			
Dollar amount of NSF grants		0.012	0.003		0.004+	0.003			
		(0.013)	(0.016)		(0.003)	(0.003)		–	–
Department and school measures									
Stayed at one school (yes = 1)			1.131***			−0.503***			0.363*
			(0.176)			(0.146)			(0.182)
Department ranking			−0.008*			−0.001			−0.005
			(0.004)			(0.003)			(0.003)
Department faculty size			0.002			0.006**			0.013*
			(0.009)			(0.002)			(0.005)
% Full faculty in department			0.014*			0.016*			−0.004
			(0.007)			(0.007)			(0.010)
% Female faculty in dept.			0.008			0.009			0.003
			(0.008)			(0.013)			(0.013)
Public university			−0.088			0.176			−0.199
			(0.202)			(0.194)			(0.232)
Constant	−10.721	−11.247	−13.449	−13.879	−14.927	−15.644	−10.964	−10.949	−11.460
N (person-years)	3,786	3,786	3,786	4,121	4,121	4,121	4,030	4,030	4,030

Note: Standard errors in parentheses.
*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ + $p < 0.10$.
Models 2–3 also include controls for graduate school publication measures. Coefficients not displayed here, but are available upon request.

the number of book chapters is a negative predictor of tenure. In English, publishing a research book and journal articles have strong positive effects, as does the average number of citations per publication. The variability in the effects of the different productivity measures across disciplines is not surprising since each discipline values different types of publications, and underscores the value of using multiple measures of productivity.

Contextual variables also have a significant influence on tenure receipt. For instance, in Sociology and English, remaining at a single school increases the likelihood of receiving tenure, and being in a higher-ranked department reduces the likelihood of tenure. In Computer Science and English, larger departments are more likely to grant tenure, and in Computer Science and Sociology, departments with higher percentages of full faculty are associated with increased tenure chances.

Overall, these results suggest that for Sociology, Computer Science, and English faculty, gender inequality exists net of productivity and departmental measures in predicting the likelihood of receiving tenure. I next show the results of decomposition analyses to test the explanatory effects of each variable representing each theoretical account.

Decomposition Analysis of Gender Gap in Tenure Rates

Models and methods

A decomposition analysis allows for a test of the relative effects of productivity, context, and career timing on the gender gap in promotion, helping evaluate the explanatory power of each set of measures. The logic behind a decomposition analysis is that it estimates the underlying factors of the gender gap by matching subsets of men and women on mean values of explanatory characteristics (productivity and context measures, in this case) and estimating the extent to which the change in the predicted probabilities of the dependent variable (tenure) are due to gender differences in the values of the explanatory measures. The results of this analysis will indicate to what extent gender difference in explanatory variables reduces the gender gap, and what portion of the gender gap in tenure is left unexplained by these measures.

This analysis uses the Fairlie decomposition technique, which extends the Blinder-Oaxaca decomposition technique to models with binary variables (Fairlie 1999, 2005).[11] The coefficients are derived from logistic regression models, where the dependent variable is 1 if the professor received tenure and 0 otherwise. Separate models are conducted to predict receiving tenure at all—at any institution, even after a possible denial—and to predict receiving tenure at the original department in which a professor began as an assistant professor. In these models, time is coded as years spent as an assistant professor, and is included because stopping and extending the tenure clock—for children or department moves—could affect tenure likelihood. All productivity measures are identical to the first analysis except they are summed to represent the total publications as an assistant professor, rather than time-varying publications. Contextual variables are measured for the starting department.

Results

The results from Fairlie decomposition analyses are displayed in table 3. All coefficients and results are from the full model with all variables, so that the relative contribution toward the gender gap is assessed net of all other measures. Within each discipline, the first model displays the results for the overall gender gap in tenure—that is, it shows the rates of tenure promotion regardless of the department, school, or duration to tenure. In Sociology, the overall gender gap in tenure rates is about 7.3 percentage points, in Computer Science it is about 5.7 percentage points, and in English it is about 6.2 percentage points. To assess tenure gaps aside from department moves, in the second model for each discipline, the dependent variable is 1 only for those who received tenure from the department in which they began as an assistant professor. In terms of receiving tenure in the original department, the gender gap in Sociology is about 9.1 percentage points, for Computer Science it is about 4.7 percentage points, and in English it is about 11.8 percentage points.

The relative impact of time, department characteristics, and productivity indicators on the tenure gap varies somewhat across departments. In Sociology, years as an assistant professor is a marginally significant predictor ($p < 0.10$) of the overall gender gap, accounting for about 20.3 percent of the gap in tenure rates. Duration remains a significant predictor ($p < 0.001$) of the gender gap in receiving tenure at the original school, and accounts for about 36.8 percent of the gender gap. This suggests that tenure delays can disadvantage for women's likelihood of receiving tenure—possibly due to negative perceptions of "stopping the tenure clock." Next, productivity accounts for a portion of the gender gap in Sociology: about 34.3 percent toward receiving tenure at all ($p < 0.05$), and about 19.8 percent of the tenure rate at the original school. Department characteristics and contextual measures do not play a significant role in the gender gap among sociologists. In Sociology, the remaining gender gap ranges from 40 to 45 percent. This implies that a substantial portion of the gender gap in promotion to tenure is from gendered processes in evaluation.

Among Computer Science faculty, time is a marginally significant predictor for receiving tenure at the original department ($p < 0.10$). For both dependent variables, productivity differences play a large role. Productivity measures contribute to between 69 and 72 percent of the gender gap in tenure rates. Department characteristics are negative predictors of the tenure gap (though not statistically significant). These negative coefficients indicate that department characteristics are predicted to widen the gender gap by between 12 and 15 percent. In other words, women are in departments in which tenure receipt is more common, but they are still less likely than men to receive tenure. The unexplained gender gap in tenure among Computer Science faculty is between 32 and 41 percent, indicating again that a large portion of the gender gap is unexplained by these measures.

Finally, among English faculty, duration as an assistant professor is a significant predictor and contributes to between 27 and 37 percent of the gender gap. This means that the fact that women take longer to receive tenure is associated with decreased chances of tenure for women relative to men. Productivity measures do

Table 3. Decomposition Analysis of Factors Explaining Gender Gap in Tenure

	Sociology		Computer Science		English	
	Received tenure at all	Received tenure at original school	Received tenure at all	Received tenure at original school	Received tenure at all	Received tenure at original school
Men's tenure rate	0.854	0.582	0.861	0.501	0.859	0.717
Women's tenure rate	0.781	0.491	0.805	0.453	0.797	0.599
Gender gap in tenure rate	0.073	0.091	0.057	0.047	0.062	0.118
Contributions from differences in:						
Years as an assistant professor	0.014+	0.033***	0.001	0.005+	0.023**	0.033***
	20.26%	36.76%	2.09%	10.68%	37.34%	27.76%
Productivity measures	0.025*	0.018	0.041***	0.033*	0.005	0.000
	34.33%	19.78%	71.93%	69.05%	8.06%	0.30%
Characteristics of department	−0.000	0.003	−0.009	−0.006	−0.022+	0.006
	−0.39%	3.56%	−15.10%+	−12.79%	−35.53%+	5.40%
All included variables	0.038	0.0544	0.033	0.0232	0.006	0.039
	54.55%	59.91%	59.07%	67.95%	10.12%	33.16%
Unexplained gender gap	45.45%	40.09%	40.93%	32.04%	89.88%	66.84%

Note: Estimates come from a Fairlie decomposition model (Fairlie 2005), with all included covariates. Decomposition coefficients are from a pooled gender model averaged over 1,500 random subsamples. $N = 383$ in Sociology, 469 in Computer Science, and 339 in English. Some professors are missing due to missing data on starting department measures. Imputed data on these measures does not change results (tables available upon request).

not explain a large portion of the gender gap for English faculty—these measures account for less than 8.1 percent of the gender difference, and are not statistically significant. Contextual measures of the department are negative predictors of the overall tenure gender gap ($p < 0.10$). Overall, 67–90 percent of the gender gap in tenure rates remains unexplained among the English faculty.

Figure 3 shows the decomposition results in graphical form, for the gender gap in receiving tenure at all. Comparing the three disciplines, we find that time is an important predictor for Sociology and English, productivity reduces the gender gap for Sociology and Computer Science, and contextual measures widen the gender gap for Computer Science and English. Across all three departments, a substantial portion of the gender gap in tenure is unexplained by these measures, and I argue can be attributed to gendered inequality in the evaluation process.

Department Prestige Changes Upon Tenure Receipt

Models and methods

The final analysis considers those who received tenure, and examines the change in the 1995 NRC department prestige rank upon tenure conferral. In this model, I regress the tenured department rank on the initial department rank, to determine if men or women move higher or lower in department rank, relative to their initial department prestige ranking. Since some individuals received tenure in a non-ranked department—for example, a liberal arts college—I use a Tobit model to account for the censoring department rank. The Tobit model conceives of the dependent variable as a latent variable that is censored for some observations below a certain threshold. In this analysis, those who received tenure in non-NRC-ranked department receive a value of 0 on the dependent variable, as do those who have not yet received tenure but have not left academia (because they are still at risk to receive tenure, they are also censored on this dependent variable). The relevant equations for the Tobit model are:

$$y_i^* = X_i\beta + \varepsilon_i \ \text{ and } \ y_i = \begin{cases} y_i & \text{if } \ y^* > \tau \\ \tau_y & \text{if } \ y^* > \tau \end{cases}.$$

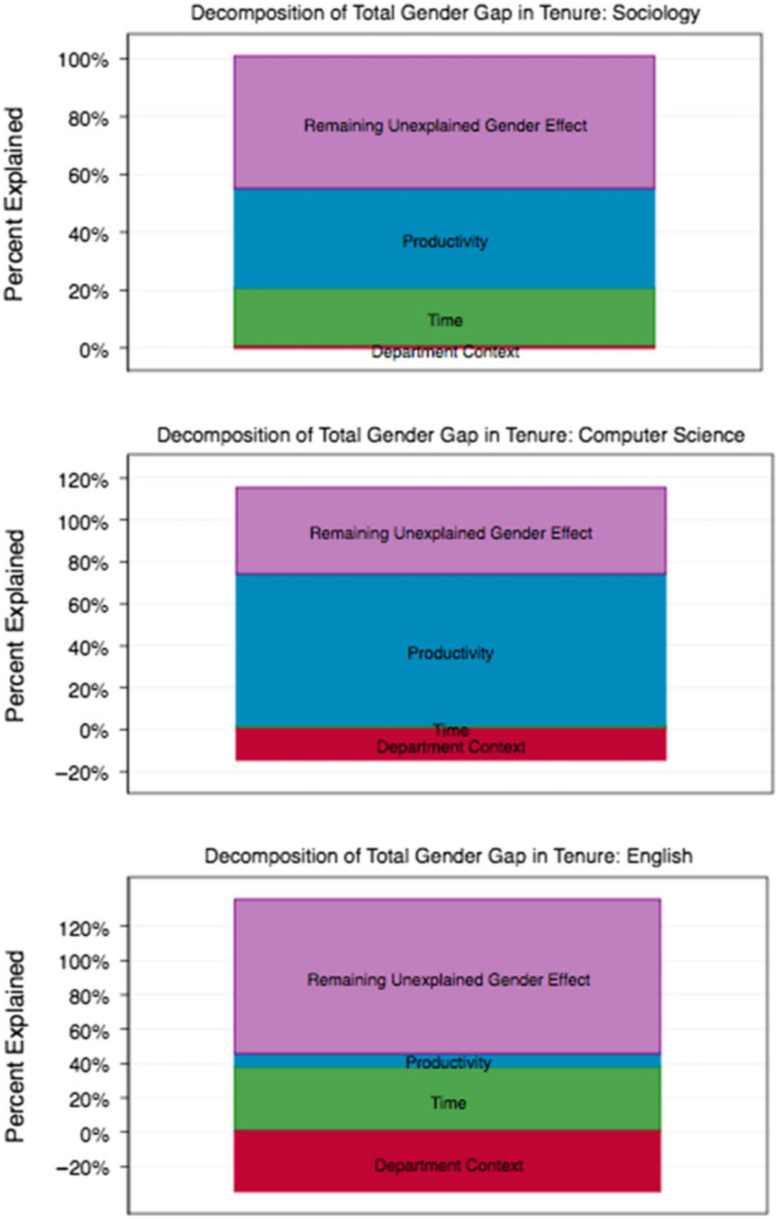
Here, y^* is a latent variable that is observed for values greater than $\tau = 0$ and censored otherwise, and $X_i\beta$ is a set of linear predictors. In Tobit regressions, the output is interpreted as the effect on the latent variable, not the observed variable.

Similar to the first analysis, the most prestigious departments have higher numerical rankings, and the lowest-ranked department has a ranking of 1. In the results, a negative coefficient indicates that individuals are moving to a department with a lower prestige ranking, and a positive coefficient indicates higher department prestige.

Results

Table 4 presents coefficients from Tobit models predicting the 1995 NRC ranking of the department in which respondents ultimately received tenure. Model 1 gives the base gender effect with no controls. Model 2 adds the independent

Figure 3. Percent of gender gap in tenure rates explained by direct gender effects and indirect effects of productivity, time, and context measures, derived from Fairlie non-linear decomposition models (see table 3)



variable of department rank for the respondent's starting assistant professorship position, as well as department and school measures.[12] Model 3 adds the same productivity controls as in the previous analysis.

Table 4. Tobit Models Predicting Rank of Tenured Department, for Sociology, Computer Science, and English Assistant Professors

	Sociology			Computer Science			English		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Independent variables									
Gender (female = 1)	−6.475* (2.548)	−6.193* (2.664)	−4.459+ (2.489)	−8.248** (3.159)	−5.912* (2.338)	−4.608* (2.337)	−14.636** (5.468)	−11.293* (5.698)	−13.810* (5.508)
Dept. rank (starting school)		−0.652*** (0.072)	−0.601*** (0.069)		0.959*** (0.039)	0.915*** (0.043)		0.477*** (0.118)	0.456*** (0.118)
Productivity measures									
Has top journal article (yes = 1)			1.756*** (0.282)			−7.826* (3.134)			−8.684 (10.862)
Number of other journal articles			11.262*** (1.731)			0.000 (0.119)			0.810 (1.218)
Number of research monograph books			8.655 (6.257)			3.942** (1.482)			3.955 (2.762)
Number of edited books			10.728* (4.186)			4.164 (4.024)			−0.505 (8.469)
Number of textbooks			1.265 (1.205)			4.456 (7.080)			–
Number of book chapters			–			−1.443+ (0.793)			−2.367 (5.723)
Num. of conference presentations			−0.092+ (0.052)			0.191** (0.062)			–
% First-/single-authored publications			1.300*** (0.329)			−0.017 (0.075)			0.289** (0.104)

(*Continued*)

Table 4. ***continued***

	Sociology			Computer Science			English		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Average citations per publication			15.558*** (3.074)			0.543** (0.192)			4.818** (1.525)
Number of NSF grants			−0.373* (0.147)			−0.773 (0.836)			–
Dollar amount of NSF grants			−0.502** (0.179)			0.055+ (0.031)			–
Dept. & school controls									
Dept. faculty size		0.148 (0.159)	0.082 (0.148)		0.026 (0.027)	0.036 (0.027)		0.520** (0.179)	0.397* (0.175)
% Full faculty in dept.		−0.040 (0.136)	0.062 (0.127)		0.057 (0.082)	0.070 (0.079)		0.146 (0.323)	0.242 (0.338)
% Female faculty in dept.		−0.034 (0.141)	0.038 (0.131)		−0.024 (0.170)	−0.041 (0.154)		0.029 (0.425)	0.103 (0.409)
Public university (=1)		1.089 (3.536)	−0.027 (3.320)		−1.861 (2.437)	−3.105 (2.479)		−33.886*** (8.206)	−29.919*** (8.208)
Constant	40.760	66.671	43.807	56.090	−5.904	−12.836	78.451	13.094	−19.098
Sigma	38.662	34.859	31.927	41.695	23.050	22.081	58.817	50.417	47.658
Observations	456	383	383	539	469	469	446	339	339

Note: Standard errors in parentheses.
*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$ + $p < 0.10$.
Models 2 and 3 also include controls for graduate school publication measures.

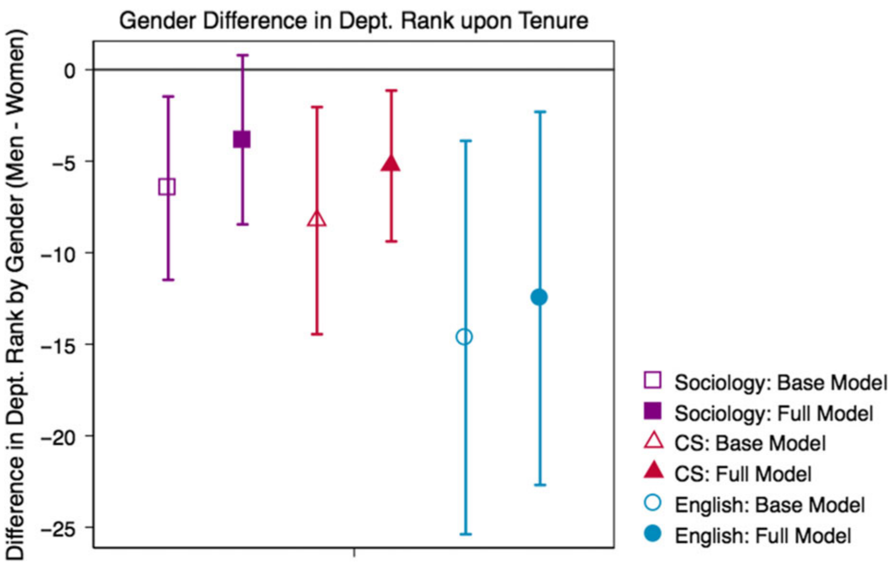
In Sociology, there is a gender effect on the latent variable of final department rank: women, on average, receive tenure in departments ranked about 6.5 positions lower than the departments where men receive tenure ($p < 0.001$). This magnitude decreases slightly with the inclusion of department characteristics measures, since women tend to be in slightly lower-ranked departments to begin with. Adding productivity measures in model 3 reduces the gender effect somewhat: net of productivity and department contextual measures, women receive tenure in departments of about 4.5 positions lower in ranking than their male counterparts ($p < 0.10$).

For Computer Science faculty, the baseline gender gap is about 8.2 prestige points, with women receiving tenure in lower-ranked departments on the latent dependent variable ($p < 0.01$). Accounting for productivity and department context in model 3 decreases the gender gap somewhat, such that women receive tenure in departments about 4.6 points lower in latent ranking than men, on average ($p < 0.05$).

Among English assistant professors, the baseline model predicts that women English professors receive tenure in departments ranked an average of 14.6 points lower than male English professors. Adding productivity and department measures in model 3 reduces the gender gap slightly, to an effect size of about 13.8 ($p < 0.05$).

Figure 4 shows the graphic representation of coefficients (Women's department rank—Men's rank) in the baseline model and the full model, with all

Figure 4. Gender difference (Women's average—Men's average) in department rank at time of tenure. Estimates derived from models without controls ("Base Model" and with full set of productivity and contextual controls ("Full Model"). Error bars indicate 95 percent confidence intervals. Higher ranking indicates a more prestigious department (maximum is 95 in Sociology, 108 in Computer Science, and 127 in English).



controls. This figure shows that the gender gap in prestige rankings narrows somewhat with controls, but even after accounting for productivity and starting department, women receive tenure in lower-ranked departments than men, on average. This result holds across disciplines. In Sociology, the full model reduces the significance level ($p < 0.10$), but in Computer Science and English departments, the gender gap remains statistically significant even after accounting for department context and productivity. Overall, this analysis suggests that not only are women disadvantaged in receiving tenure at all, but when they do receive tenure it is in lower-ranked departments than men, on average. I argue that these results suggest that vertical sex segregation across department prestige is produced in part by gender differences in tenure processes.

Conclusion and Discussion

This paper examines the extent to which the gender gap in promotion to tenure is due to three theoretical explanations: gender differences in productivity, in organizational context, or gendered inequality in the evaluation process. The study uses a unique longitudinal dataset with the career histories of former assistant professors in Sociology, Computer Science, and English, containing more detailed measures of publication productivity and department characteristics than have previously been available. The results presented here show that women are not only disadvantaged in their likelihood of receiving tenure overall, but are less likely to receive tenure in the departments where they began their assistant professor careers. Women also receive tenure in less prestigious departments than men in their fields, on average. A decomposition analysis demonstrates that the gender gap in promotion to tenure is only partially explained by differences in productivity, and that contextual factors either widen the gap or do not significantly predict the gap. A sizeable portion of the gender gap in tenure is unexplained by productivity and variation in department context, suggesting that gendered inequality in evaluation affects the gender gap. In adjudicating between the three predominant theoretical explanations, results suggest that gender inequality in evaluation is the leading culprit for women's lower promotion rates, though productivity plays a role as well.

It should be recognized that gender is not the only identity that can contribute to inequality in career progression, and this study does not cover the academic domain in its entirety. Importantly, I am unable to examine the extent to which other characteristics, including race/ethnicity, immigrant status, and sexual orientation, shape career trajectories. It is likely that gender could interact with these statuses to produce greater inequality along these dimensions—a process that might additionally vary by discipline. Furthermore, this study examines career outcomes among individuals who successfully gained a tenure-track position in a research university; inequality in access to these positions—and the trajectories of individuals who are situated in other academic environments—is a key endeavor for future research. The gender gap in tenure that I observe in this sample may be narrow in magnitude compared to gendered processes in the broader academic system. It is important to consider that gender may play a role in other aspects of academia, including PhD completion, pursuing an academic career, obtaining a first job, and promotion beyond tenure (see Long, Allison, and McGinnis 1993; Misra, Kennelly, and Karides 1999; Weeden, Thébaud, and Gelbgiser 2017).

These findings lead to additional questions. It would be ideal to have a wider range of fields, to test how disciplinary context influences the gender gap in tenure. I find that the levels of gender inequality in tenure rates are somewhat consistent across the three departments studied. One disciplinary difference pertains to the contribution of productivity in explaining the gender gap: in English departments, productivity predicted only a small proportion of the gender gap, a higher percent in Sociology, and the highest in Computer Science. The explanatory power of productivity is inversely related to the unexplained gender gap in tenure, which I find is highest in English departments and lowest in Computer Science departments. These results imply that feminization of departments and/or disciplinary context can influence both gender gaps in productivity inputs and their predictive power in evaluation processes. To systematically test these differences, future studies could examine a larger number of disciplines.

Of course, there are other productivity outputs that factor into tenure decisions. Importantly, this study would benefit from data on teaching and university service work. Drawing from existing scholarship, I posit that at the research universities in my sample, grants and publications tend to be weighted more heavily than teaching and service work (see Pyke 2014). Further, research has demonstrated that women tend to exhibit higher levels of university service work and put more time into teaching than men, on average (see Fox 2005; Pyke 2014), suggesting that these measures could in fact widen the gender gap in outcomes rather than reducing it.

Beyond teaching and service, readers will be able to think of additional measures that are not included here: for instance, internal and external grants, awards, invited talks, book publisher prestige, and subfield. In supplementary appendix analyses, I have coded these measures from CVs for the Sociology sample, and find that this host of measures explains an additional 3.8 percent of the tenure gap (see appendix 2). Additional variables that could not be coded from existing data would need to hold certain parameters to change the patterns identified in this paper: significant gender differences; an independent effect net of existing measures; and predictive power of tenure receipt. Based on these criteria and simulated data (available upon request), I maintain that it is implausible for additional productivity measures to greatly reduce the unexplained portion of the gender gap, though it would be valuable to test this proposition with future data collection endeavors.

Further, publication measures themselves may exhibit gender biases, as researchers have demonstrated through work on self-citations (see King et al. 2016). Women could be disadvantaged in collaborative work, or could partake in different types of work (for instance, more qualitative research in sociology), which might influence publication likelihood (see Leahey 2007). This study cannot distinguish between possible causes of gender differences in publications. It would be worthwhile to supplement outcome-based measures of productivity with time-use data and perceptions of productivity.

Is the remaining inequality in tenure outcomes—unexplained by these productivity and context measures—a result of bias or other gendered processes? Existing scholarship suggests that the observed inequality likely does not stem from motivated bias, but rather that subtle and/or unconscious gender biases interfere with objective evaluations of research productivity (Moss-Racusin et al. 2012; Steinpreis, Anders, and Ritzke 1999). Overly scrutinizing women's work, questioning research contributions, and differences in recommendation levels are examples of subtle gender processes that can culminate in different evaluations of women compared to men (Leahey 2007; Madera, Hebl, and Martin 2009; Misra, Lundquist, and Templer 2012; Moss-Racusin et al. 2012). Gender differences in visibility and social networks might also play a role: how well known is the scholar, and how does this translate into external reviews for the tenure process? These types of factors could push borderline cases in one direction or another. Further, the observed career moves that are correlated with gender could be due to both supply- and demand-side processes. Testing precise mechanisms that contribute to the unexplained gender gap in tenure would require additional survey data to complement this study. Future studies could examine the role of family demands and parental status, tenure evaluation results, reasons behind career changes, and to what extent gender differences in these dimensions have consequences for both productivity and career progress.

The results of this study have both theoretical and applied implications for understanding the reasons behind the gender gap in promotion more generally. The findings suggest that there are multiple sources behind the gender tenure gap in academia, which indicate multiple paths toward reducing gender inequality. Women's underrepresentation in high-status positions extends to a wide range of contexts, including medicine, law, politics, finance, and more. In these other settings, productivity measures tend to be less precise than in academia. It is therefore not unreasonable to speculate that similar processes might apply to an even greater extent in professions outside academia, in part because without precise productivity measures, it is easier for gender to color promotion evaluations. In future research, it would be valuable to test how these theoretical explanation influence women's representation and career progression in other occupational domains.

This paper uses innovative data to estimate the levels of gender inequality in promotion to tenure in three academic fields, and results suggest that women in academia face disadvantages due to gendered inequality in tenure evaluation processes. To reduce gender inequality, cultural interventions within departments and institutions will likely be more fruitful than individual-oriented strategies aimed at helping women become more productive, and a multifaceted approach could be the most promising solution. The findings from this study could contribute to developing precise solutions to gender inequality in promotion, with the goal of academia becoming a leading domain for the advancement of gender equality and inclusion.

Notes

1. Since the mid-1990s, the Internet Archive has preserved the information that existed on the website in earlier years. See www.archive.org/web. (Internet Archive 2016)
2. In Computer Science, I counted 195 total women assistant professors in the schools in my sample. I oversampled women to gain accuracy in estimating gender differences.
3. The 2000–2004 time frame includes faculty who were assistant professors at any stage of their pre-tenure career during these years. This time period was chosen so that I had a long enough period to observe the majority of tenure outcomes.
4. The e-mail survey questionnaire is available upon request, and was sent to professors with any missing information. The number of professors surveyed and response rates were 100 (43.0 percent) in Sociology, 109 (67.9 percent) in Computer Science, and 167 (85.0 percent) in English. Some respondents did not answer all questions, which is why the non-response rates do not exactly match the rates shown in appendix table A1.
5. For instance, if I know that a professor is currently an associate professor with tenure, I can infer that he/she did receive tenure, and can impute the time-to-tenure based on the sampling year and other available information.
6. The benefit of using Google Scholar is that it allows me to obtain publication data for those with missing CVs, and that it standardizes what is "counted" as a publication. To ensure accuracy of publication data, the Google Scholar publications were validated in multiple ways and cross-checked with CVs when possible. See appendix 1.
7. In Computer Science, the last author position is used, as this is generally reserved for the primary contributor.
8. It should be noted that prestige rankings from the 1995 NRC data do contain some error. See Paxton and Bollen (2003).
9. Gender was coded two ways: first, by hand-coding the gender of the person as I observed from their name and/or photo on their departmental website, and second, by using a name-matching program.
10. This squared term serves to model the curvilinear function of the likelihood of receiving tenure as time increases.
11. In Computer Science, eight professors who were assistant professors for only two years (and then left academia) are excluded from the decomposition models, since the models would not converge otherwise.
12. In the Tobit models 2 and 3, some individuals drop out of the sample due to missing data on their starting department rank, which occurs if they began at an unranked school and moved into the NRC sample.

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Supplementary Material

Supplementary material is available at *Social Forces* online.

References

Becker, Gary S. 1985. "Human Capital, Effort, and the Sexual Division of Labor." *Journal of Labor Economics* 3:S33–58.

Bielby, William T., and James N. Baron. 1986. "Men and Women at Work: Sex Segregation and Statistical Discrimination." *American Journal of Sociology* 91(4):759–99.

Booth, Alison L., Marco Francesconi, and Jeff Frank. 2003. "A Sticky Floors Model of Promotion, Pay, and Gender." *European Economic Review* 47(2):295–322.

Castilla, Emilio J. 2008. "Gender, Race, and Meritocracy in Organizational Careers." *American Journal of Sociology* 113(6):1479–1526.

Cech, Erin. 2013. "The Self-Expressive Edge of Occupational Sex Segregation." *American Journal of Sociology* 119(3):747–89.

Charles, Maria, and David B. Grusky. 2004. *Occupational Ghettos: The Worldwide Segregation of Women and Men*, vol. 200. Stanford, CA: Stanford University Press.

Correll, Shelley J. 2004. "Constraints into Preferences: Gender, Status, and Emerging Career Aspirations." *American Sociological Review* 69(1):93–113.

Cotter, David A., Joan M. Hermsen, Seth Ovadia, and Reeve Vanneman. 2001. "The Glass Ceiling Effect." *Social Forces* 80(2):655–81.

Cotter, David A., Joan M. Hermsen, and Reeve Vanneman. 2011. "The End of the Gender Revolution? Gender Role Attitudes from 1977 to 2008." *American Journal of Sociology* 117(1):259–89.

Fairlie, Robert W. 1999. "The Absence of the African-American Owned Business: An Analysis of the Dynamics of Self-Employment." *Journal of Labor Economics* 17(1):80–108.

———. 2005. "An Extension of the Blinder-Oaxaca Decomposition Technique to Logit and Probit Models." *Journal of Economic and Social Measurement* 30:304–16.

Fox, Mary F. 2005. "Gender, Family Characteristics, and Publication Productivity among Scientists." *Social Studies of Science* 35(1):131–50.

Ginther, Donna K., and Kathy J. Hayes. 1999. "Gender Differences in Salary and Promotion in the Humanities." *American Economic Review* 89(2):397–402.

Gorman, Elizabeth H., and Julie A. Kmec. 2009. "Hierarchical Rank and Women's Organizational Mobility: Glass Ceilings in Corporate Law Firms." *American Journal of Sociology* 114(5):1428–74.

Internet Archive. "Internet Archive Wayback Machine." Last accessed July 2016. https://archive.org/web/.

Jacobs, Jerry A. 1989. *Revolving Doors: Sex Segregation and Women's Careers*. Stanford, CA: Stanford University Press.

———. 1998. "Measuring Time at Work: Are Self-Reports Accurate?" *Monthly Labor Review* 121:42.

King, Molly M., Carl T. Bergstrom, Shelley J. Correll, Jennifer Jacquet, and Jevin D. West. 2016. "Men Set Their Own Cites High: Gender and Self-Citation across Fields and over Time." *arXiv preprint arXiv:1607.00376*.

Leahey, Erin. 2006. "Gender Differences in Productivity: Research Specialization as a Missing Link." *Gender & Society* 20(6):754–80.

———. 2007. "Not by Productivity Alone: How Visibility and Specialization Contribute to Academic Earnings." *American Sociological Review* 72(4):533–61.

Long, J. Scott. 1978. "Productivity and Academic Position in the Scientific Career." *American Sociological Review* 43:889–908.

Long, J. Scott, Paul D. Allison, and Robert McGinnis. 1993. "Rank Advancement in Academic Careers: Sex Differences and the Effects of Productivity." *American Sociological Review* 58(5):703–22.

Long, J. Scott, and Robert McGinnis. 1981. "Organizational Context and Scientific Productivity." *American Sociological Review* 46:422–42.

Lundquist, Jennifer H., Joya Misra, and KerryAnn O'Meara. 2012. "Parental Leave Usage by Fathers and Mothers at an American University." *Fathering* 10(3):337.

Madera, Juan M., Michelle R. Hebl, and Randi C. Martin. 2009. "Gender and Letters of Recommendation for Academia: Agentic and Communal Differences." *Journal of Applied Psychology* 94(6):1591.

Manchester, Colleen Flaherty, Lisa M. Leslie, and Amit Kramer. 2010. "Stop The Clock Policies and Career Success in Academia." *American Economic Review* 100(2):219–23.

Mason, Mary Ann, Nicholas H. Wolfinger, and Marc Goulden. 2013. *Do Babies Matter? Gender and Family in the Ivory Tower*. New Brunswick, NJ: Rutgers University Press.

McNamee, Stephen J., and Robert K. Miller. 2009. *The Meritocracy Myth*. Lanham, MD: Rowman & Littlefield.

Misra, Joya, Ivy Kennelly, and Marina Karides. 1999. "Employment Chances in the Academic Job Market in Sociology: Do Race and Gender Matter?" *Sociological Perspectives* 42(2):215–47.

Misra, Joya, Jennifer Hickes Lundquist, and Abby Templer. 2012. "Gender, Work Time, and Care Responsibilities among Faculty." *Sociological Forum* 27(2):300–323. Blackwell Publishing Ltd.

Moss-Racusin, Corinne A., et al. 2012. "Science Faculty's Subtle Gender Biases Favor Male Students." *Proceedings on the National Academy of the United States of America* 109(41):16474–79.

National Research Council. 2010. *A Data-Based Assessment of Research-Doctorate Programs in the United States*. Washington, DC: National Academies Press. http://www.nap.edu/readingroom.php?book=researchdoc&page=tables.html (1995 rankings); http://www.nap.edu/rdp/ (2006 variables).

Paxton, Pamela, and Kenneth A. Bollen. 2003. "Perceived Quality and Methodology in Graduate Department Ratings: Sociology, Political Science, and Economics." *Sociology of Education* 76:71–88.

Perna, Laura W. 2005. "Sex Differences in Faculty Tenure and Promotion: The Contribution of Family Ties." *Research in Higher Education* 46(3):277–307.

Probert, Belinda 2005. "'I Just Couldn't Fit It In': Gender and Unequal Outcomes in Academic Careers." *Gender, Work & Organization* 12(1):50–72.

Pyke, Karen D. 2014. "Faculty Gender Inequality and the 'Just Say No to Service' Fairytale." In *Disrupting the Culture of Silence: Confronting Gender Inequality and Making Change in Higher Education*, edited by Kris De Welde and Andi Stepnick. pp. 83–95. Sterling, VA: Stylus Publishing.

Ragins, Belle Rose, Bickley Townsend, and Mary Mattis. 1998. "Gender Gap in the Executive Suite: CEOs and Female Executives Report on Breaking the Glass Ceiling." *Academy of Management Executive* 12(1):28–42.

Reskin, Barbara, and Patricia A. Roos, eds. 1990. *Job Queues, Gender Queues: Explaining Women's Inroads into Male Occupations*. Philadelphia: Temple University Press.

Ridgeway, Cecilia L. 2011. *Framed By Gender*. Oxford: Oxford University Press.

Sax, Linda J., Linda Serra Hagedorn, Marisol Arredondo, and Frank A. DiCrisi. 2002. "Faculty Research Productivity: Exploring the Role of Gender and Family-Related Factors." *Research in Higher Education* 43(4):423–46.

Stack, Steven 2004. "Gender, Children, and Research Productivity." *Research in Higher Education* 45(8):1–30.

Steinpreis, Rhea E., Katie A. Anders, and Dawn Ritzke. 1999. "The Impact of Gender on the Review of Curricula Vitae of Job Applicants and Tenure Candidates: A National Empirical Study." *Sex Roles* 41:509–28.

Weeden, Kim A., Sarah Thébaud, and Dafna Gelbgiser. 2017. "Degrees of Difference: Gender Segregation of US Doctorates by Field and Program Prestige." *Sociological Science* 4:123–50.

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.

Winslow, Sarah 2010. "Gender Inequality and Time Allocations among Academic Faculty." *Gender & Society* 24(6):769–93.

Xie, Yu, and Kimberly A. Shauman. 2003. *Women in Science: Career Processes and Outcomes*, vol. 26, no. 73.4. Cambridge, MA: Harvard University Press.