INVESTIGATION OF GENDER AND RACE EFFECTS ON PROMOTION IN DEPARTMENTS OF GEOGRAPHY IN THE UNITED STATES

by

Jackson B. Pickett

A dissertation submitted to the Graduate Council of
Texas State University in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
with a Major in Geographic Information Science
December 2015

Committee Members:

Yongmei Lu, Chair

David R. Butler

Frederick A. Day

Jonathan Wivagg

Qiang Zhao

FAIR USE AND AUTHOR'S PERMISSION STATEMENT

DEDICATION

…when the age is in, the wit is out.

William Shakespeare, *Much Ado about Nothing*, Act III, Scene V.

For all those at Texas State University who encourage excellence at all ages.

ACKNOWLEDGEMENTS

This adventure would not have been possible without the support of my committee: Professors Lu, Butler, Day, Wivagg, and Zhao. Many others in the Department of Geography aided in the development of this research - to mention a few: Professors Dixon, Giordano, and Tiefenbacher. Thanks to my guide through the bureaucratic maze, Ms. Allison Glass-Smith. The professional appearance of the questionnaire and the mailing documents reflect the work of Cortney Jean Akers and Jolane A Wiegand of the Texas Print and Mail Service. This project would have been impossible without the Association of American Geographers' *Guide to Geography Programs in North America* and the archive of these directories at Meridian Place in Washington, DC where Reacha O'Neal and many others aided my search for information. Thanks too to all who filled out and returned the questionnaire which I sent out; your effort made this research possible. Margaret Vaverek and the research librarians of Alkek Library were universally helpful in my quest for sources of information about a professor's career. Isabel Canette, PhD of StataCorp LP provided valuable insights into the use of Stata software.

TABLE OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Abbreviation	**Description**
Admin	Hours per week spent in administrative work
Amount	Amount in dollars of contract or grant funding
AscP	Associate professor
AssP	Assistant professor
AscPCites	Cumulative citations when promoted to become associate professor
AscPPubs	Cumulative publications when promoted to become associate professor
AscPYrs	Years between granting of PhD and promotion to become an associate professor
Child< 6yrsAscP	Number of children under the age of six while an assistant professor
ChildNum< 6yrs	Number of children under the age of six
ChildTotalAscP	Total number of children while an assistant professor
ChildTotalProf	Total number of children while an associate professor
CEEWISE	Committee on the Education and Employment of Women in Science and Engineering
Contract	Dummy variable indicating presence of contract or grant funding
Demo	Usually vote for Democratic Party
DolYr	Dollars per year in contract or grant funding
EarlyBaby	Infant born within five years after PhD granted
EarlyBabyDummy	Dummy variable, coded 0 or 1, for early baby
EarlyBabyNum	Number of early babies
Full	Spouse or partner works full-time
Geog	Research focus in geography
HireCites	Cumulative citations when hired as an assistant professor
HirePubs	Cumulative publications when hired as an assistant professor
HiringInstitutionCode	Code given to institution hiring assistant professor
Human	Percentage of time spent on human geography
Legal	Marriage sanctioned by law

MovePhD	Move as assistant professor to PhD-granting institution
NumMoves	Number of moves as an assistant professor
None	Spouse or partner does not work
Other (hours)	Hours per week spent other activities
Other (%)	Percentage of time spent other subdisciplines
PhD<89	PhD granted before 1989
PhD89 97	PhD granted between 1989 and 1997
PhD>97	PhD granted after 1997
PhDHire	Years between granting of PhD and hiring as an assistant professor
PhDHire(1), PhDHire(2)	Two transforms of PhDHire variable
Phys	Percentage of time spent on physical geography
Prof	Professor, typically a full professor
ProfCite	Cumulative citations when promoted to become a full professor
ProfPubs	Cumulative publications when promoted to become a full professor
Region	Percentage of time spent on regional geography
Research	Hours spent per week in research
South	Southern region of United States
STEM	Science, technology, engineering, and mathematics
Teach	Hours spent per week teaching
TopAssP	Assistant professor hired by top-ranked institution
TopPhD	PhD granted by top ranked institution
Total	Total number of hours spent at work
US Birth	Born in the United States
West	Western region of United States
White	White or Caucasian race
Years	Years of contract or grant funding

ABSTRACT

This study sought evidence of differences in academic promotion associated with gender or race within the discipline of geography in the United States. Professors were identified between 1991 and 2007 using the Association of American Geographers' *Guides and Directories*. For each institution, males were matched to female assistant professors based on the year their PhD was granted; the ratio of males to females was about 7 to 4. A total of about 848 assistant professors were identified and traced until about 97% to 98% were promoted. The key outcome variable for these matched cohorts was years until promotion. Cox regression was used as it is designed to analyze survival data and can incorporate multiple variables. Even corrected for publications and other variables, the gender and white race coefficients were significant and demonstrated that the rate of promotion for females was about 25% slower than of males and the rate of promotion for whites was about 35% slower than that of other races. In terms of years, females were about 0.4 years slower to be promoted to become associate professors than males and associate professors of the white race were about 1.7 years slower to be promoted to become full professors than other races. This study provides evidence of that academic promotion may be influenced by both gender and race.

1. INTRODUCTION

An odd alliance between the National Women's Party and Congressman Howard W. Smith of Virginia added the word "sex" to a bill that became the 1964 Civil Rights Act, which banned "discrimination on the basis of race, color, religion, sex, or national origin" (Bird 1997, 149; Civil Rights Act of 1964 § 703, Pub L No 88-352, 78 Stat 255 (1964), codified at 42 USC §§ 2000e-1 et seq (1988); Whalen and Whalen 1985, 115). The National Women's Party was frustrated by forty years spent in a fruitless advocacy of the Equal Rights Amendment to give women of "equality of rights under the law" (Ginsburg 1973, 1013). It was certainly odd that National Women's Party turned to Representative Smith as he was a dedicated foe of civil rights for racial minorities (Bird 1997, 149-153; Whalen and Whalen 1985, 116). Nonetheless Congressman Smith added "sex," gambling that this addition would act as booby trap blocking passage of the 1964 Civil Rights Act (Bird 1997, 149-153; Franklin 2012, 1318n36; Whalen and Whalen 1985, 116). An advocate of the bill, Congressman Celler attempted to save the Civil Rights Act from Smith's booby trap by opposing the amendment, but predictably Congresswomen defended the addition of "sex" by pointing out that white men and blacks, both men and women, would be treated equally under the 1964 Civil Rights Act, but not white women (Bird 1997, 155-158; Whalen and Whalen 1985, 116-117). Congresswoman St. George stated, "… we are entitled to this little crumb of equality. The addition of the little, terrifying word 's-e-x' will not hurt this legislation in any way" (Whalen and Whalen 1985, 117). As Congressman George Meader pointed out, Congressman Smith had "…outsmarted himself. At this point there was no way you could sink the bill" (Whalen and Whalen 1985, 117). The combination of support by the National Women's Party and the majority's support of banning gender discrimination in employment produced a majority favoring passage, which Congressman Smith joined, and the bill passed 290 to 130 in the House and later became the law of the land (Bird 1997, 158-160). At long last discrimination in employment on the basis of gender was illegal.

However, up to 1972, a chair of a department could legally send a letter stating, "Your qualifications are excellent, among the best we've seen. But frankly, we're looking for a man for this position. I hope you won't consider that discrimination" (118 Cong Rec 5811 (1972)). Discrimination on the basis of gender in hiring was illegal, but educational institutions initially were exempted from the Civil Rights Act of 1964, or Title VII, (§ 703, 78 Stat 255). At the time courts were reluctant to infringe on the academic freedom of educational institutions and gave them little attention in matters of academic employment; this soon ended (Byrne 1989, 254; Pacholski 1992, 1318). Six years later Congress collected evidence of gender discrimination in educational institutions (Rubin 1981, 737). Doctor Rossi presented evidence about

> men and women whose employment has "always" been academic, and compare[d] the ascent to the pinnacle of full professorship of men holding social science doctorates with that of single women and of married women. *After twenty years of an academic career, 90 per cent of the men had reached a full professorship, something achieved by only 53 per cent of the single women and 41 per cent of the married women*. From these data it seems clear that it is sex and not the special situation of married women that makes the greatest difference to career advancement

(Murray 1971, 264). In addition Congress heard from Professor Harris who reported that

> [a]t Columbia, we tried the crude but we think useful procedure of simply counting the numbers of men and women on the faculty in full-time positions who received their PhDs in the 1960s and then studying their

> distribution by rank. There were 195 male faculty at Columbia who received doctorates in the 1960s. 47% are assistant professors, 38% are associate professors and 15% are full professors. There are 25 women full-time faculty at Columbia in the same category. 96% (24) are assistant professors, one is an associate professor (tenure granted this year, PhD 1961); there are no female full professors who obtained their PhD in the 1960s at Columbia. Well over 50% of the men who earned their PhDs in 1963 and 1964 have been given tenure. None of the women in that group has been promoted to the rank of associate professor with tenure, although one woman is an assistant professor with tenure, an anomaly brought about by the extreme reluctance of her department to promote her. These differences in promotion rates are too great for discrimination against women not to be a large part of the story

(Murray 1971, 265). Congress also received evidence that females lagged males in academic rank nationwide (118 Cong. Rec. 5804-5805 (1972); see Table 1).

Table 1. Rank of Females in American Higher Educational Institutions.

American Council on Education

	University		4-Year College	
Rank	Male	Female	Male	Female
Assistant	29%	31%	31%	32%
Associate	24%	15%	23%	17%
Professor	30%	10%	22%	11%

Simon and Grant's Digest of Educational Statistics (1969)

Rank	Male	Female
Assistant	28%	29%
Associate	22%	16%
Professor	24%	9%

Swayed by an impressive array of studies, Congress concluded that

> in the area of sex discrimination, women have long been invited to participate as students in the academic process, but without the prospect of gaining employment as serious scholars. When they have been hired into educational institutions, particularly in institutions of higher education, women have been relegated to positions of lesser standing than their male counterparts. In a study conducted by Theodore Kaplow and Reece J. McGee, it was found that the primary factors determining the hiring of male faculty members were prestige and compatibility, but that women were generally considered to be outside of the prestige system altogether

(HR Rep No 92-238, 92d Cong, 2d Sess 19-20 (1971), in 1972 USCCAN 2137, 2155). The evidence supported the conclusion that women were discriminated against on the basis of gender and Congress ended the educational institution exemption with the Equal Employment Opportunity Act of 1972 (Pub L No 92-261, 86 Stat 103, codified at 42 USC § 2000e-1 (1988)). How could this legislation be used to gain a legal remedy?

2. LITERATURE REVIEW

2. A. Theories Guiding Investigation

The law provides a basic framework, or theory, to test cases for the presence of gender and racial discrimination. Under the law there are two basic types of discrimination cases: (1) disparate treatment cases and (2) disparate impact cases (Paetzold and Wilborn 2012, 2-4; Player 2013, 51-52). Each will be briefly reviewed in a simplified fashion, but first some definitions. Legally, discrimination involves treating people differently because of their protected class, such as gender or sex (Paetzold and Wilborn 2012, 2; Player 2013, 45). The "because of" part of the definition of discrimination requires evidence of intent (Paetzold and Wilborn 2012, 2; Player 2013, 50-51). The actual evidence of intent is often circumstantial, but needs to convince the judge or jury that the employer, the defendant, acted in a way that harmed the plaintiff, the professor, because of her protected class and that other reasons for the harmful behavior are unlikely (Paetzold and Wilborn 2012, 2; Player 2013, 51, 215). Two models, or sets of related ideas, identify the steps involved in disparate treatment or disparate impact litigation. Often it is easier to understand legal concepts after they are illustrated by cases.

Percy H. Green, a Black civil rights activist working for McDonald Douglas Corp., took part in a "stall-in" where cars were stalled to block Brown Road preventing the morning shift-change employees from going to work at McDonald Douglas Corp. (McDonald Douglas Corp. v. Green, 411 U.S. 792, 794 (1973)). As a result of this action and probably others, Mr. Green was fired by McDonald Douglas Corp., but three weeks later he applied to be rehired in response to a McDonald Douglas Corp. job opening ad and was rejected (411 U.S. 796). Mr. Green then asserted that he had been denied employment based on his race (411 U.S. 796). As expected McDonald Douglas replied that Mr. Green had not been rehired because of his prior illegal activity. The Supreme Court held that Mr. Green must be given the opportunity to show that the stated reason for not being re-hired, his illegal activity, is a "pretext for a racially discriminatory decision, such as by showing that whites engaging in similar illegal activity were retained or hired …" (411 U.S. 793). This case forms the basis of a disparate treatment discrimination case.

McDonald Douglas Corp. v Green illustrates the basic steps, or model, which start with the plaintiff asserting their "prima facie" case consisting of showing that he belonged to a protected class, he was qualified for the job he applied for, but was rejected, and the position remained open (McDonald Douglas Corp. v. Green, 411 U.S. 792-793 (1973); Paetzold and Wilborn 2012, 8; Player 2013, 51, 168-169). Next, the employer defends by offering "a bona fide occupational qualification reasonably necessary to the normal operation of that particular business" (42 USC §2000e-2(e)) as an explanation for their seeming discrimination (Paetzold and Willborn 2012, 9; Player 2013, 177-181). Last, the plaintiff attacks by showing pretext, or that "the proffered reason was not the true reason for the employment decision" (Paetzold and Willborn 2012, 9-10; Player 2013, 181-183; Texas Dept. of Community Affairs v. Burdine, 450 U. S. 248, 256 (1981)). The strength of the evidence is evaluated by the jury or judge.

In *Griggs v. Duke Power Co.*, 401 U.S. 424, 427-428 (1971), the employer required power-plant workers to have a high school diploma and a passing score on an intelligence test. Requiring a high school diploma or passing score on an intelligence test prevented many more blacks from being employed than whites and in addition Duke Power Co. had a history of failing to hire blacks (401 U.S.424, 425-426 (1971)). In its defense Duke Power Co. could not provide evidence that either hiring requirement was related to job performance (401 U.S. 424, 425-426 (1971)). The Supreme Court ruled that these two requirements were barriers to employment and not valid requirements for employment (401 U.S. 424, 436 (1971)). The Griggs v. Duke Power Co. case became a model of a disparate impact discrimination case where: (1) the plaintiff identifies a criterion which the employer used to hire or promote employees which hindered the protected group and (2) the criterion did not further the employer's business interests (401 U.S. 431-432 (1971); Paetzold and Willborn 2012, 33; Player 2013, 215-216).

Much of the evidence presented in discrimination cases is circumstantial (Player 2013, 167). In the *Griggs v. Duke Power Co.* case (401 U.S. 424, 431 n. 6 (1971)) simple descriptive statistics were used to show that only 12% of blacks vs. 34% of whites had graduated from high school and only 6% blacks vs. 58% whites had acceptable test scores. This established that the job requirements had a disparate impact on a protected group (Paetzold and Willborn 2012, 35; Player 2013, 218). The law has evolved a general guideline that

> statistics showing racial or ethnic imbalance are probative in a case … only because such imbalance is often a telltale sign of purposeful discrimination; absent explanation, it is ordinarily to be expected that nondiscriminatory hiring practices will in time result in a work force more or less representative of the racial and ethnic composition of the population in the community from which employees are hired. Evidence of long-lasting and gross disparity between the composition of a work force and that of the general population thus may be significant even though … Title VII imposes no requirement that a work force mirror the general population

(International Broth. of Teamsters v. U. S., 431 U.S. 324, n. 20 (1977)). So, how big does the difference need to be a "telltale sign" of discrimination? The Equal Employment Opportunity Commission has established a "4/5ths rule" or

> [a] selection rate for any race, sex, or ethnic group which is less than four-fifths (4 /5) (or eighty percent) of the rate for the group with the highest rate will generally be regarded by the Federal enforcement agencies as evidence of adverse impact, while a greater than four-fifths rate will generally not be regarded by Federal enforcement agencies as evidence of adverse impact

29 C.F.R. § 1607.4(d). A refinement of EEOC's 4/5ths rule is the two to three standard deviation rule which uses standard deviations to measure the differences between proportions and takes in to account the effect of sample size (Paetzold and Willborn 2012, 210-213; Player 2013, 223-226). How can an employer defend against a claim that race or gender impeded hiring or promotion?

One defense is to claim that multiple factors influence hiring, promotion, or salary levels. In *Bazemore v. Friday*, 478 U.S. 385, 397-399 (1986), black employees claimed they were paid less than white employees and used multiple regression with race, education, experience, and job title as their independent variables and salary as the dependent variable. Their employer, the Extension Service of North Carolina State University, convinced a lower court that the absence of some variables in the regression model, such as the difference in pay according to the county within the state, rendered the regression equation results inadmissible as evidence (Bazemore, 478 U.S. 385, 399-400 (1986)). The Supreme Court rejected this contention (Bazemore, 478 U.S. 385 (1986)) and held that the regression model was admissible, even if the failure "to include all variables affected probativeness of the analysis." Once regression models were admissible into evidence in a court, statistical expert witnesses began to debate: (1) which variables to include (Finkelstein 1980, 738-739); (2) the appropriateness of the data; (3) the method of analysis; and (4) the results (McReynolds v. Sodexho Marriott Services, Inc., 349 F.Supp.2d 1 (D.D.C. 2004)). Over time the legal system incorporated multivariate regression which provides a sophisticated way to detect racial or gender discrimination.

The outcomes contested in discrimination cases often involve salaries where multiple linear regression has been used and is successful in estimating how much discrimination reduces salaries (Paetzold and Willborn 2012, 266). But how about hiring or promotion which are binary and not the usual real number expected as the dependent variable in linear regression (Meyers, Gamst, and Guarino 2006, 148). Initially linear regression was used, but gradually litigants have introduced evidence in hiring or promotion cases from logistic regression (Paetzold and Willborn 2012, 182-184, 332-337) attempting to relate gender or race to a reduced probability of hiring or promotion. A few cases, such as those involving age discrimination, have presented evidence from survival analysis (Paetzold and Willborn 2012, 342). Only rarely has the legal system considered how different cohorts might affect the results of legal analysis (Finkelstein 1980, 748-749; Peterson 2003, 154, 156; Piette and Thornton 1995, 69; *Segar v. Smith* 738 F.2d 1249, 1263-1264 (1984)).

The legal theory of gender or racial discrimination in academic promotion is useful as it: (1) defines discrimination; (2) provides models or types of discrimination, such as disparate treatment and disparate impact, which guide the collection of evidence to support or refute a claim of discrimination; (3) suggests a criterion to use to detect discrimination, like the 4/5the rule or the 2 to 3 standard deviation rule used to compare proportions; (4) accepts statistical evidence, such as multivariate regression where the optimal set of variables is selected and then the effect of adding gender is evaluated; and (5) suggests some of the variables to use in a discrimination case when applied to academic promotion, such as years of experience and publications. Where the legal theory fails is that it has not evolved an optimal set of variables to use in statistical tests, like multiple-regression analysis, in the context of discrimination in academic promotion. Why? The most important reason is that courts defer to university or college's academic freedom and allow promotion decisions to be made with a minimum of review (Chase 2007, 169-171; Dekat 2009, 276; Hora 2001, 356; Loh 1992, 429-430; Moss 2006, 22). This limitation of the legal theory of discrimination in academic promotion forces the consideration of other theories.

Economic theory has many possible applications to discrimination in academic promotion with an obvious one being the supply and demand for academic professors (Marschke, et al. 2007, 2). Academic professors gain skills and experience over time, or human capital, which can enhance their attractiveness in the market (Becker 1993, 17-21; Kolpin and Singell 1996, 408; Krugman and Wells 2013, 532). Hesli and Lee (2011, 394) have identified some variables which reflect human capital, such as quality of PhD-granting institution, academic subfields, to which could be added years of experience, research funding, and publications. This gain in human capital could be offset by losses due to aging (Goodwin and Sauer 1995, 742-743). Opportunity costs, or the value of what is given up (Krugman and Wells 2013, 7-8), in an academic setting can be seen in how time is allocated between teaching, service, and research (Hesli and Lee 2011, 394;

Taylor, Fender, and Burke 2006, 856-857). Further, the opportunity cost of time spent in administrative service can be important; for example, acting as a department head tends to result in fewer publications (Goodwin and Sauer 1995, 740). Choice of how to allocate time also includes family structure where the timing and number of children might influence the allocation of time between academic and family responsibilities (Hesli and Lee 2011, 394).

Feminist theories envision that males maintain their unearned privileges by creating a work environment which hinders the realization of the full potential of female faculty (Marschke, et al. 2007, 2-3). How to hinder women:

> gender-biased performance evaluations, use of gender-biased student evaluations, demanding tenure criteria and short tenure clocks that favor male faculty, retention offers and salary counter offers that reward mens' mobility, tokenism and hidden workloads, inadequate mentoring and networking opportunities, competitive rather than collaborative styles, hostility towards pregnancies and families, and the devaluation of certain disciplines and types of research

(Marschke, et al. 2007, 2-3). Feminist theory suggests several variables to include in an analysis of academic promotion including time to tenure, moves to other institutions, marital status, number of children and their ages, focus of research, and allocation of time to research.

Institutional theories posit that the proportion of women faculty varies by type of higher educational institution (Marschke, et al. 2007, 3-4). Generally as institutional prestige increases the proportion of women faculty decreases (Kolpin and Singell 1996, 420-421; Marschke, et al. 2007, 3-4). Variables that could be used to estimate institutional prestige would include ranking of PhD-granting institution and ranking of current institution, number of publications and their citations, and research funding

(Marschke, et al. 2007, 3-4). Even a brief review of some of the theories attempting to explain discrimination suggests many variables which could be important in predicting academic promotion.

2. B. Models, Methods, and Major Findings

The theories of discrimination in academic promotion naturally lead to regression models to search for variables that predict academic promotion. The general strategy is to evolve regression models which incorporate variables which successfully predict promotion and see if gender or race is significant once the effect of other variables is accounted for. A separate issue concerns methods and specifically research design. A simple research design is to examine the academic ranks of males and females at a given time. This cross-sectional data is easy to collect, but ignores the effect of time. Longitudinal studies follow professors over time. Even better, some longitudinal studies follows cohorts of professors over the time it takes for academic promotion to occur. With the switch from cross-sectional to longitudinal studies, the method of statistical analysis shifts from multivariate linear regression to multivariate logistic and Cox regression. Logistic regression has a binary dependent variable which fits academic promotion. Cox regression uses time to a binary event as the dependent variable which is a step better than logistic regression, as it incorporates time to the occurrence of a binary event such as time to promotion. The literature concerning discrimination in academic promotion is extensive and will be briefly reviewed starting with the variables used to predict academic promotion.

The difference in demographic variables between academic males and females has been studied extensively. Most studies (see Table 2 in the APPENDIX) show female faculty members are about the same age as males (Bayer 1973; Ginther and Hayes 2003, 39; Ginther and Kahn 2004, 200; Ginther and Kahn 2006, 24), but make up a minority of academic faculty (Bayer 1973; Cataldi, Bradburn, and Fahimidi 2005, 16; Nettles, Perna, and Bradburn 1993, 25; Raymond, Sesnowitz, and Williams 1993, 205). As expected advancing age favors promotion (Astin and Bayer 1972, 116; Bayer and Astin 1975, 798; Ginther and Hayes 2003, 51; Ginther and Kahn 2004, 203-205; Ginther and Kahn 2006, 33). Many studies show fewer females have been promoted or gained tenure (Bayer and Astin 1975, 798; Ginther 2001, 20; Ginther and Kahn 2004, 199; Nettles, Perna, and Bradburn 2000, 5; Raymond, Sesnowitz, and Williams 1993, 209; Zelinsky 1973, 157-158). Other studies report small differences between males and females (Bayer and Astin 1968, 194; Ginther and Hayes 2003, 50; Ginther and Kahn 2006, 12; Long, Allison, and McGinnis 1993, 711).

For both male and female faculty the dominant race was white which made up about 89% to 95% (Bayer 1973, 14; Nettles, Perna, and Bradburn 2000, 25); there were a few percent more white males than white females (see Table 2 in the APPENDIX). More black females than black males were members of the faculty in several studies (Bayer 1973; Ginther and Hayes 2003, 39; Ginther and Kahn 2006, 24) with no difference in others (Ginther and Kahn 2004, 200; Nettles, Perna, and Bradburn 2000, 25). Fewer blacks were promoted (Ginther and Hayes 2003, 50; Ginther and Kahn 2004, 205-206; Ginther and Kahn 2006, 36; Nettles, Perna, and Bradburn 2000, 29) and some studies suggest more Asians males and females are promoted (Nettles, Perna, and Bradburn 2000, 29). For other races the differences between males and females are less consistent which may reflect the small number of faculty in these categories (Bayer 1973; Nettles, Perna, and Bradburn 2000, 29).

The regional distribution of female faculty has shifted dramatically between the 1970s and the 2000s with male and female now favoring the Northeast corridor, Great Lakes, and West Coast reflecting the abundance of institutions of higher education in densely populated urban areas (Kulis and Sicotte 2002, 14-15). Bayer and Astin (1975, 798) used multivariate regression and found that residing in the Great Lakes and Plains region favored gaining tenure for males and females. The proportion of foreign born faculty is 17%-27% with no consistent difference by gender or of its effect on promotion (Ginther and Hayes 2003, 39; Ginther and Kahn 2004, 200; Ginther and Kahn 2006, 24). How gender preferences for certain regions change the chance of promotion have received limited attention.

Males and females differed in some of their employment variables as shown in Table 2 in the APPENDIX. The proportion of males and females receiving their PhD from a top ranked program increased from about 30% in the 1990s to nearly 80% in the 2000s with females trailing males by a few percent (Ginther and Hayes 2003, 39; Ginther and Kahn 2004, 200; Ginther and Kahn 2006, 24; Long, Allison, and McGinnis 1993, 710); this had no consistent effect on promotion (Ginther and Hayes 2003, 43; Ginther and Kahn 2004, 202; Ginther and Kahn 2006, 36; Long, Allison, and McGinnis 1993, 711). A few studies have found that increasing time between PhD and hiring reduces the chance of promotion (Ginther and Hayes 2003, 40; Long, Allison, and McGinnis 1993, 711). Inbreeding, or professors who worked at their PhD-granting institution, was uncommon, about 20% of the total, with no difference between males and females (Long, Allison, and McGinnis 1993, 710). In some studies inbreeding slowed promotion (Hargens and Farr 1973, 1396-1397; McGee 1960, 486-487) but in others had no effect on promotion (Long, Allison, and McGinnis 1993, 711). About 20% to 40% of both male and female professors worked at a top-tier university (Ginther and Hayes 2003, 39; Ginther and Kahn 2004, 200; Ginther and Kahn 2006, 24) with a highly variable effect on their chance of promotion (Ginther and Hayes 2003, 44; Ginther and Kahn 2004, 202; Ginther and Kahn 2006, 36; Long, Allison, and McGinnis 1993, 711).

In terms of time allocation, females spent more time teaching and males more time in research (Bayer 1973; Manchester and Barbezat 2013, 61; Nettles, Perna, and Bradburn 2000. 91-95; Winslow 2010, 779; Xie and Shauman 1998, 865-868; see Table 2 in the APPENDIX). Differences in time spent in administration or total hours worked failed to show a consistent difference between male and female faculty (Bayer 1973, Ceci et al. 2014, 76; Jacobs and Winslow 2004, 149), but may favor promotion (Astin and Bayer 1972, 106-108). The studies reviewed failed to detect a clear effect of time allocation on the chance of promotion.

Across a wide variety of academic disciplines many studies show fewer females are promoted and their promotions take longer (Ginther and Hayes 2003, 39, 54; Ginther and Kahn 2004, 204-209; Hesli, Lee, and Mitchell 2012, 481, 490; Kaminski and Geisler 2012, 865; Long, Allison, and McGinnis 1993, 711; Nettles, Perna, and Bradburn 2000, 6, 29; Perna 2001, 550; Roos and Gatta 2009, 183; Table 2 in the APPENDIX). The largest difference in the proportion of females promoted occurs in economics (Ginther and Kahn 2004, 200) even though no difference is found in Arts and Sciences (Roos and Gatta 2009, 187) or engineering and science (Kaminski and Geisler 2012, 865). Females fared better in the time to promotion where females were no more than one year behind males in the time it took to be promoted (Ginther 2001, 9; Ginther and Hayes 2003, 40; Ginther and Kahn 2004, 209; Ginther and Kahn 2006, 12-13; Kaminski and Geisler 2012, 865; Long, Allison, and McGinnis 1993, 711-712). Some of the differences in the proportion and rate of promotion may reflect differences in productivity variables.

Two consistent findings emerge from studies of publications: (1) males publish more (Astin 1972, 378; Bayer 1973; Ceci et al. 2014, 103-105; Cole and Zuckerman 1984, 224; Fox 2005, 135; Fox and Faver 1985, 542; Ginther and Kahn 2006, 24, Hesli, Lee, and Mitchell 2012, 478; Levin and Stephan 1998, 1056; Nettles, Perna, and Bradburn 2000, 5, 29; Xie and Shauman 1998, 856) and (2) publications increase the chance of promotion (Astin and Bayer 1972, 106-108; Ferber and Green 1982, 563; Ginther and Hayes 2003, 52; Ginther and Kahn 2004, 202; Ginther and Kahn 2006, 37; Hesli, Lee, and Mitchell 2012, 480-482; Long, Allison, and McGinnis 1993, 711; McElrath 1992, 275; see Table 2 in the APPENDIX). Ferber and Green (1982, 554) report that gender differences in publication frequency vary by discipline, but without a clear pattern. Other studies show differences favoring males which vary in degree and may not be statistically significant (Fox and Faver 1985, 542; Ginther and Hayes 2003, 40; Ginther and Kahn 2004, 200; Levin and Stephan 1998, 1056-1057; McElrath 1992, 274; Snell et al. 2009, 288). Publications favor promotion, but in McElrath's study (1992, 275) this was only true for females and not true for engineers in Ginther and Kahn's study (2006, 37). Citations of papers by males and females are about the same, although the number of citations has no significant effect on the chance of promotion (Ginther and Kahn 2004, 200, 202; Long, Allison, and McGinnis 1993, 710-711).

Likewise publications or citations before being hired as an assistant professor have no effect on promotion (Long, Allison, and McGinnis 1993, 710-711). Malesare more likely to be funded (Bayer 1973; Nettles, Perna, and Bradburn 2000, 8, 40) and receive more funds (Ferber and Green 1984, 558). Gender differences in the number of moves are not consistent with Ginther and Kahn (2006, 24) reporting women have more employers and McElrath (1992, 274) and Rosenfeld and Jones (1987, 501) reporting more moves by males . Moves might be more difficult depending on the family structure.

Most studies show malesare more likely to be married (Astin and Milem 1997, 131, 143; Bayer 1973; Fox and Faver 1985, 542; Ginther 2001, 8; Ginther and Hayes 2003, 40; Goulden, Mason, and Frasch. 2011, 151; Hesli, Lee, and Mitchell 2012, 479; Long, Allison, and McGinnis 1993, 710; Mason and Goulden 2004, 92; Rudd et al. 2008, 232-233) and some studies show that marriage has a positive effect on the chance of promotion (Ginther 2001, 20; Long, Allison, and McGinnis 1993, 711; Rudd et al. 2008, 233-234; see Table 2 in the APPENDIX). Rudd et al. (2008, 233-234) report that the effect of marriage is positive if your spouse is not working full-time, although Ginther and Hayes (2003, 51) and Hesli, Lee, and Mitchell (2012, 482-483) report no significant effect of marriage on promotion. More women have working spouses and spouses working full-time (Bayer 1973; Jacobs and Winslow 2004, 155; Macfarlane and Luzzadder-Beach 1998, 1612; Rudd et al. 2008, 233). Bayer (1973) and Perna (2005, 288) find males and women are equally likely to have spouses working at a university or at their university, but Astin and Milem (1997, 132-133, 151) and Jacobs and Winslow (2004, 155) report more women are married to a faculty member and this increases their chance of promotion (Astin and Milem 1997, 132-133, 151).

Almost all studies show maleshave more children than wo (Fox and Faver 1985, 542; Ginther and Hays 2003, 40; Ginther and Kahn 2006, 24; Goulden, Mason, and Frasch. 2011, 151; Hargens, McCann, and Reskin 1978, 158; Jacobs and Winslow 2004, 153; Long, Allison, and McGinnis 1993, 710; Mason and Goulden 2004, 99; Perna 2005, 288; Sax et al. 2002, 431; Stack 2004, 917; see Table 2 in the APPENDIX). Only two studies show an equal proportion of male and female professors have children (Ginther and Kahn 2004, 200; Hargens et al. 1978, 158). The effect of children on the chance of promotion is highly variable with: (1) a positive effect being reported by Ginther and Hayes (2003, 51) and Ginther and Kahn (2006, 27); (2) no effect (Ginther and Kahn 2004, 205; Long, Allison, and McGinnis 1993, 714; Sax et al. 2002, 434); and (3) a negative effect for women (Astin and Bayer 1972, 111). More males than women have early babies, or babies born within five years after the professor's PhD was awarded; an early baby reduces the chance women will gain tenure (Mason and Goulden 2002, 24-25). As expected, males have more young children, or children under the age of six, than women (Fox and Faver 1985, 542; Ginther and Kahn 2004, 200; Ginther and Kahn 2006, 4, Table 1; Long, Allison, and McGinnis 1993, 710; Morrison et al. 2011, 538), but usually young children have no effect on the chance a professor will be promoted (Long, Allison, and McGinnis 1993, 714; Morrison 2011, 550), although Ginther and Kahn (2004, 205; 2006, 27) report a positive effect which varies with the statistical model.

Males and women approach their job searches differently. When considering a job offer, women are twice as likely, 29% vs. 15%, to be influenced by the new position being good for their spouse (Bayer 1973, see Table 2 in the APPENDIX). In terms of job location, women are more concentrated in large metropolitan areas (Kulis and Sicotte

2002, 15; Marwell, Rosenfeld, and Spilerman 1979, 1226-1228; Rosenfeld and Jones 1987, 501-502), even though living in a large metropolitan area reduces a professor's chance of promotion (Kulis and Sicotte 2002, 19-20). Urban areas often are dominated by the Democratic Party (Kim, Elliott, and Wang 2003, 741) which may in part explain why in the twentieth century American faculty members, especially in the humanities and social sciences, have been overwhelmingly liberal in their views and Democratic in their voting (Cardiff and Klein 2005, 249, 253; Hamilton and Hargens 1993, 608; Ladd and Lipset 1975, 225-228; Lipset 1959, 461-462; Lipset 1982, 144; Lipset and Ladd 1972, 71; Rothman, Lichter, and Nevitte 2005; Turner and Hetrick 1972, 571). Recent studies show women are less conservative and more likely to vote for the Democratic Party than males are (Bayer 1973; Cardiff and Klein 2005, 249, 252; Zipp and Fenwick 2006, 314-315). Faculty members with liberal or Democratic political views tend to gather in more highly ranked colleges and universities (Hamilton and Hargens 1993, 613; Ladd and Lipset 1975, 139-148; Lazarsfeld and Thielens 1958, 162; Lipset 1982, 145-146; Zipp and Fenwick 2006, 311-312). For example in 1969 low-quality universities had 39% liberal faculty, medium-quality universities had 45% liberal faculty, and high-quality universities had 52% liberal faculty (Hamilton and Hargens 1993, 613); similar results were found in 1955 (Ladd and Lipset 1975, 138-139). Further, liberal professors publish more and have higher professional status (Lipset and Ladd 1972, 82). Rothman, Nevitte, and Lichter (2005, 10-12) used multivariate regression to show that the Republican political-party affiliation variable had a statistically significant negative coefficient with an index measuring the quality of the school where the professors taught. Astin and Bayer (1972, 111) found that a conservative political view had a negative effect on academic rank in both males and women. In sum, women are more liberal in their views and favor the Democratic Party in their voting more than males do, and there is limited but only suggestive evidence that political views may influence academic advancement (Ames et al. 2005), although few recent studies have been done to evaluate this possibility. This suggests that research variables including political voting patterns might be useful in predicting academic promotion. As theory suggested research variables, research variables may guide the selection of a research design.

Given the wide variety of variables which may influence academic promotion it would be ideal if a litigant could introduce into evidence an actual experiment or a randomized prospective study where, for example, males and women were randomly given academic jobs and then their success in gaining promotion measured (Rothman, Greenland, and Lash 2008, 88-92; Spector 1981, 7-8). Such studies are available in trials of drugs or medical treatments, but are not available in discrimination cases (Juni, Altman, and Egger 2001, 42; Rothman, Greenland, and Lash 2008, 88-92). Lacking actual experimental studies or randomized prospective studies, the typical research designs are cross-sectional studies or longitudinal studies (Menard 2002, 2). Cross-sectional studies involve collecting data on all subjects at about the same time, while a longitudinal study involves sampling at least at two different times (Menard 2002, 2). Longitudinal studies could involve sampling: (1) different people at successive times, a repeated cross-sectional study; (2) the same people at different times, a panel study; (3) the same people at different times where the people are similar in age, a birth-cohort study (Menard 2002, 2-4); or (4) matched cohorts which are similar on several variables used to match the groups (Rothman, Greenland, and Lash 2008, 174-175). The analysis of cross-sectional or longitudinal studies could include comparisons of descriptive statistics or various forms of multiple regression (Paetzold and Willborn 2012, 210, 272; Player 2013, 208, 211).

Many studies have been published which present evidence relevant to the possibility of gender discrimination in academic promotion and a review of cross-sectional studies is shown in Table 3 in the APPENDIX. Most cross-sectional studies are descriptive and show a highly variable reduction in the proportion of women compared to males gaining tenure or promotion to the rank of associate professor, labeled Associate in Table 3 in the APPENDIX, or full professor; often this difference in the proportion becomes more pronounced with increasing rank (Alpert 1989, 12; Astin and Bayer 1972, 105, 107; CEEWISE 1979, 83; Ginther 2001, 8; Ginther and Hayes 2003, 39; Ginther and Kahn 2004, 200; Long 2001, 172; Long, Allison, and McGinnis 1993, 708; Luzadder-Beach and Macfarlane 2000, 412; Macfarlane and Luzzadder-Beach 1998, 1592; Nettles, Perna, and Bradburn 2000, 5-6; Perna 2001, 550; Roos and Gatta 2009, 183; Szafran 1983, 1114-1115; Toutkoushian 1998, 57). Regression analysis was done on a few of the cross-sectional studies and also showed a highly variable reduction in the chance a woman would be promoted relative to that of a man from 3% to 51% (Ginther 2001, 20-23; Ginther and Hayes 2003, 49-53; Hesli, Lee, and Mitchell 2012, 481-483; Perna 2001, 551-552). The difference in the promotion rate between females and males was not consistent in cross-sectional regression and descriptive studies (see Table 3 in the APPENDIX).

Longitudinal studies seeking evidence of gender discrimination in academic promotion using linear regression are outlined in Table 3 in the APPENDIX. Ginther and

Kahn (2004, 197-200) used two sources of data to construct their longitudinal databases: (1) the 1973-2001 Survey of Doctoral Recipients of 320 economists and included 227 males and 93 females who had academic-tenure track positions and (2) American Economic Association (AEA) Directory listings of economics PhDs who were assistant professors at PhD-granting institutions in the United States and Canada and included 93 males and 95 females. The Survey of Doctoral Recipients lacks data about publications except for the 1983, 1995, and 2001 surveys, although it contains professors with PhDs granted between 1972 and 1991 (Ginther and Kahn 2004, 198-199). The dataset based on the American Economic Association's Directory was limited to professors who were granted their PhDs in the 1980s, but included productivity and other information (Ginther and Kahn 2004, 198-199). Ginther and Kahn (2004, 201-202) reported results using linear regression on the American Economic Association dataset, noting that logistic regression gave the same results, which showed that, even corrected for publications and other variables, females were 13% less likely than males to gain tenure within ten years after receiving their PhDs. A similar analysis was done by Ginther and Kahn (2004, 204-205) on the Survey of Doctoral Recipients of economists in the United States and found females 15% less likely to be promoted than males using linear regression of many variables, including publications. Smaller differences were reported by Ginther (2001, 21) and Ginther and Hayes (2003, 51) as shown in Table 3 in the APPENDIX. Similar studies were done comparing linear and logistic regression.

The outcome variable in academic gender discrimination cases often is binary, promotion or the gaining of tenure, which is a good fit for logistic regression. Several studies have compared linear and logistic regression (see Table 3 in the APPENDIX).

Ginther (2001, 5-7) performed linear and logistic regression on data from the 1973-1997 Survey of Doctorate Recipients dataset which included PhDs awarded between 1972 and 1989, who were on a tenure track, and had complete data for at least eight years. Tenure dates were available from 1973 to 1991 and imputed thereafter (Ginther 2001, 7). Similarly publication data was available in the 1983 and 1995 surveys; when necessary an average was used (Ginther 2001, 8). Both linear and logistic regression using multiple variables, including publications, show females 7% to 9% less likely to be promoted (Ginther 2001, 20-21; see also Table 3 in the APPENDIX). Ginther and Hayes (2003, 36-37) used Survey of Doctorate Recipients of humanities PhD recipients from 1975 to 1989, although after 1991 the year tenure was gained was imputed as the first year when the professor was noted to be tenured; this means the imputed year of tenure might be slightly longer than the actual date of tenure. Ginther and Hayes (2003, 37-38, 70) also note that the Survey of Doctorate Recipients in the humanities has cumulative publications at the time tenure was gained, but only for 1983 and 1987 to 1995. Using logistic regression with variables including publications, Ginther and Hayes (2003, 49-50) find that females are 7% less likely to be promoted than men. Long, Allison and McGinnis (1993, 707) followed a cohort of biochemistry assistant professors who received their PhDs between 1956 and 1967. Long, Allison, and McGinnis (1993, 711, 716) used logistic regression to adjust the probability of promotion according to variables such as the number of publications and reported females had a 10% lower probability of being promoted to become an associate professor and a 20% lower probability of being promoted to become a professor; neither difference is statistically significant. Long (2001, 16-18, 282-283) used the Survey of Doctorate Recipients between 1973 and 1995 and the Survey of Earned Doctorates between 1920 and 1995 to collect data on about ten to twenty thousand scientists and engineers. Using logistic regression, Long (2001, 165-166, 171-179) found that even correcting for age, career field and type of employer, but not for publications or other measures of productivity, that females lagged males in gaining tenure by about 17% in 1979, and 4% to 6% in 1989 and 1995. Similarly Long (2001, 176-179) found that females lagged males in being promoted to full professor by about 20% in 1979 and about 9% in 1995.

Male and female professors can be compared with survival curves which graph the probability of promotion as a function of time. Both linear and logistic regression studies ignore the element of time and typically compare the promotion or tenure rate at one point in time. By including time explicitly it is possible to show the effect of gender over time. A summary of the results of these studies is shown in Table 3 in the APPENDIX. Using the Survey of Doctoral Recipients with no corrections for publications, Ginther and Kahn (2004, 208-209) analyzed survival curves and found no significant difference in the promotion rates for males and females in life sciences, physical sciences, political sciences. The two statistically significant exceptions were engineering where females were a little more likely to be promoted than males and economics where females were 21% less likely to be promoted ten years after receiving their PhD (Ginther and Kahn 2004, 208-209). Again using the 1973 to 2001 Survey of Doctorate Recipients with variables including publications, Ginther and Kahn (2006, 12-13) compared the survival curves of males and females and found males were slightly less likely to be promoted. Survival curves can also be adjusted for relevant variables.

The Cox proportional hazards regression model can be used to compare the time to promotion or tenure in male and female professors and adjust the survival curves for relevant variables such as the number of publications (see Table 3 in the APPENDIX). Ginther and Hayes (2003, 53-56) used a proportional hazards regression model and found that the hazard ratio of promotion was less for females in comparison to men, varying from 077 to 0.82, after correcting for demographic and productivity variables. The hazard of promotion at a given time point is the instantaneous rate of the change in the probability of promotion given you have not yet been promoted and the hazard ratio is the ratio of female and male hazard functions; a hazard function gives the rate of change of a conditional probability (Kleinbaum and Klein 2005, 9-12; described further in METHODS). Similarly, Ginther and Kahn (2004, 201) used proportional hazards regression analysis including productivity and other variables and found females 25% less likely to gain tenure within ten years of receiving their PhD in their longitudinal cohort of economics professors; no hazard ratio was given. Ginther and Hayes (2003, 53-56) extended this analysis to the humanities where they found females were less likely to be promoted than males with hazard ratios ranging from 0.778 to 0.824. Likewise, Ginther (2001, 5-11, 22-23) studied professors identified in the 1973-1997 Survey of Doctorate Recipients who received their PhDs in science between 1972 and 1989 and reported hazard ratios varying from 0.868 to 0.940 with females being less likely to be promoted than men. A different endpoint was used by Kaminski and Geisler (2012, 864-865). They followed 2996 assistant professors between 1990 and 2009 and determined the number of years they spent in an academic job and found males and females had nearly identical Kaplan-Meier survival curves and were promoted at the same rate (Kaminski and Geisler 2012, 864-865).

Many factors could potentially influence how quickly male and female professors gain tenure or are promoted. Some of these factors, or variables, are known and others await discovery; even with extensive study regression only explains about 34% to 59% of the total variability of the response variable (Ahern and Scott 1981, 62; Ginther and Kahn 2004, 202; Zar 210, 340). Matching studies represent an attempt to control for, or reduce, the effect of variables not included in the research variables, but possibly related to the matching variables, such as age or employing institution, on the chance of gaining tenure or a promotion (see Table 3 in the APPENDIX). Marwell, Rosenfeld, and Spilerman (1979, 1227-1228) matched 207 males to 207 females based on the age when they were awarded their PhDs, employment status in clinical work or not, and the quality of their PhD-granting institution. The outcome (Marwell, Rosenfeld, and Spilerman 1979, 1228-1229) was that females reside in urban areas with larger population and are less mobile than men. Bernard (1966, 263-264) selected 28 males and 28 females by approximately matching the males to the females according to: (1) discipline (zoology), (2) PhD-granting institution, (3) year when their PhD was awarded, (4) having 10 to 15 years of academic experience, and (5) academic institutional affiliation. She then compared the male and female professors and found that they were nearly identical in their productivity of articles, chapters, and papers (Bernard 1966, 266-269). Ahern and Scott (1981, 12) used the 1979 Survey of Doctorate Recipients to select two males for each woman and matched them according to: (1) year of their PhD, (2) field of PhD study (3) PhD-granting institution, and (4) race. Most of the males and females received their PhDs in the 1940s and 1950s and nearly 70% had an academic job when they were surveyed in 1979 (Ahern and Scott 1981, 12-13). In all the cohorts studied females were less likely to be promoted or gain tenure than males (Ahern and Scott 1981, 18-19, 25-27, 32-33, 45-46). The Survey of Doctorate Recipients in 1979 lacked information about citations or publications (Ahern and Scott 1981, 50) so regression including these variables was not possible. Linear regression was used to evaluate the effect of gender in gaining higher academic rank, where 1 = instructor and 4 = full professor, after correcting for demographic, employment, and family variables; in all cases females were at a disadvantage (Ahern and Scott 1981, 53-59). Matched cohort studies have not been used to see if publications or other variables, such as publications, influence the chance of gaining tenure or promotion.

2. C. Limitations of the Literature and Potential Contribution of this Study

Each type of study design has advantages and limitations; some will be reviewed here. Cross-sectional studies have the advantage of being relatively easy to conduct: survey a population of professors, determine their academic ranks and gender, and then compare the proportions at each rank and use multivariate regression to adjust for variables other than gender which might influence academic promotion. A typical result, mentioned above, is that: (1) PhDs in economics granted to females rose from less than 10% in 1970 to over 25% in 2000 (Ginther and Kahn 2004, 195) and (2) during the same period the proportion of female full professors in economics only increased from about 2% in 1970 to about 7% in 2000 (Ginther and Kahn 2004, 196). The problem with comparing proportions of males and females at a given time is that one often is comparing a mix of older males and younger female professors. What looks like gender discrimination might be explained by demographic inertia or age-cohort effects.

Starting with demographic inertia, assume that: (1) all academic faculty are hired at age 30; (2) all faculty work until they retire at age 65; and (3) the number of new faculty hired equals the number which retire each year (Hargens and Long 2002, 496). Next, imagine a world where there was no change in the total number of faculty members, a steady state where females made up 20% of the faculty at all ages from 30 to 65, and then suddenly the number of female PhDs increased to 50% and remained at 50% indefinitely, with 50% of the new hires being females (Hargens and Long 2002, 496). Given these assumptions an increase in the proportion of female faculty to half of the total faculty would take 35 years due solely to demographic inertia (Hargens and Long 2002, 496). Further, the time it takes to reach equilibrium is not sensitive to the age structure of the faculty or an increase or decrease in total faculty positions, although the initial rate of change is sensitive to the faculty age structure and changes in total number of faculty positions (Hargens and Long 2002, 498-499). A steady increase in the proportion of female PhDs, which has been seen (Long 2001, 35-40), will lead to an increase in the difference between the proportion of females with PhDs and proportion of female faculty (Hargens and Long 2002, 499). Clearly marked differences between the proportion of female PhDs and female professors, in isolation, does not prove gender discrimination. In fact Shaw and Stanton (2012, 3736) have shown that demographic inertia is an important factor in explaining the paucity of females in fields as diverse as mathematics and sociology. So, one limitation in the interpretation of cross-sectional studies is demographic inertia.

As a result of demographic inertia, comparisons of proportions of males and females at different academic ranks in a cross-sectional study could be misleading. Given the steady increase in the number of female PhDs, male faculty would be both older and hired many years before the female faculty they would be compared with, potentially producing age-cohort differences (Menard 2002, 79; Shaw and Stanton 2012, 3736). Age effects in academic promotion are obvious (Long 2001, 162-163), but age-cohort effects could be equally important (Menard 2002, 7-8, 11). Differences in age cohorts could show up in many ways with one example being the supply and demand for PhDs in the academic market, where a glut of PhDs would lead to a smaller fraction of PhDs being hired (Perrucci, O'Flaherty, and Marshall 1983, 431). Probably less obvious is that PhDs hired during unfavorable market conditions also are slower to gain promotion and are more productive before they are promoted in comparison to faculty hired when the demand is high relative to the supply of PhDs (Perrucci, O'Flaherty, and Marshall 1983, 446). This would tend to alter the relationship between productivity variables and promotion creating an age-cohort effect. This would make it difficult for multivariate regression of a cross-sectional sample of faculty members to disentangle potentially confounding effects of age, age-cohort, and gender.

Many of the very best studies investigating the possibility of gender discrimination in academic promotion are based on the Survey of Doctorate Recipients (Ahern and Scott 1981, xv; CEEWISE 1979, 151; Ginther 2001, 5-8; Ginther and Hayes 2003, 36-38; Ginther and Kahn 2004, 197-199; Long 2001, 16-20). The Survey of Doctorate Recipients started in 1973 and is conducted every other year (CEEWISE 1979, 151). It stratifies the population of PhDs and samples with sample size varying with the size of the strata, to give an overall sample size of 79,400 in 1977 (CEEWISE 1979, 151). In 1977 64% responded to the questionnaire giving study size of 50,600 PhDs (CEEWISE 1979, 151). More recently the overall survey response rate is 94% to 98% (Henderson, Clarke, and Reynolds 1996, 137). The Survey of Doctorate Recipients in 1979 included questions about age, gender, place of birth, educational background, marital status, children and their ages, employment experience, how work time is allocated, salary, academic rank, degree and employment specialization (CEEWISE 1979, 90-93). What is missing in many years is any information about productivity, such as publications (Ginther 2001, 8). The lack of productivity information forced Ginther (2001, 8) to "impute the average productivity measures" using data from the 1983 and 1995 Survey of Doctorate Recipients data. Long (2001, 179) concluded that "the information on productivity … is too aggregated over time to be used in predicting promotion." Since one of the main goals of this study is to analyze the effect of gender on academic promotion, then studies based on the Survey of Doctorate Recipients data need to be replicated with more complete data on productivity, as measured by publications.

If acceptance of studies based on data from the Survey of Doctorate Recipients was viewed as conditional, then what studies would remain? As Table 4 in the APPENDIX shows most of the remaining studies use a cross-sectional experimental design. The limitations of cross-sectional studies have been reviewed above. Long, Allison, and McGinnis's (1993) is a model study, but might be unrepresentative of fields other than biochemistry. Kaminski and Geisler's (2012, 865) remarkable study focused on retention of faculty, but lacks data on factors or variables related to promotion. Last, Bernard's (1966 263-267) carefully matched cohort study is limited by its small size, 28 professors in each group, and only focused on differences in academic productivity and did not consider promotion.

In addition to forbidding gender discrimination, federal law requires affirmative action to increase the representation of minorities and females in educational faculties (Anonymous 1979, 879; 41 C.F.R. §§ 60-2.1 to 2.4 (1977)). The practical meaning of affirmative action varies from encouraging minorities and females to apply for academic positions to explicit preferences for the hiring of minorities and females (Merritt and Reskin 1997, 202). Even though Title VII specifically forbids discrimination on the basis of gender or race (Civil Rights Act of 1964 § 703, Pub L No 88-352, 78 Stat 255 (1964), codified at 42 USC §§ 2000e-1 et seq (1988)), the Supreme Court carved out an exception: In 1979 the Supreme Court held that "Title VII's prohibitions against racial discrimination does not condemn all private, voluntary, race-conscious affirmative action plans" (United Steelworkers of America, AFL-CIO-CLC v. Weber, 443 U.S. 193 (1979)). Affirmative action plans were adopted by many institutions of higher education, due in part to their fear of losing federal funding (Galles 2004, 17). The goal of affirmative action plans is to selection and promotion of faculty which reflect the diversity of race and gender seen in the United States, but to be effective affirmative action risk reverse discrimination (Munro 1995, 565; Wolf-Devine 1993, 228). How might affirmative action risk reverse discrimination? As Kekes (1993, 144) points out the strong form of affirmative action favors "altering the procedural rules so as to favor some people in order to increase the likelihood that they rather than others will achieve the desired position." If females were strongly favored over males in promotion then their chance of promotion would be increased despite their relative lack of qualifications favoring promotion; this would be a form of reverse discrimination. Note that everyone is part of a legally "protected class" as gender or sex includes males and females and race includes blacks and whites, among others (Schwartz 2000, 657-658). So far the risk of reverse discrimination is more hypothetical than real (Burstein 1991, 511; Loeb, Ferber, and Lowry 1978, 218) and the many studies reviewed above suggest that the real problem is the persistence of discrimination in academic promotion, perhaps due to the lack of effectiveness of these affirmative action programs (Feinberg 1984, 168; Hanna 1988, 409; Loeb, Ferber, and Lowry 1978, 219).

Over the many years since the enactment of the Civil Rights Act of 1964 support for preferential treatment, via affirmative action, seems to be waning. Currently four members of the Supreme Court; Chief Justice Roberts, and Justices Scalia, Thomas and Alito; agree that "[t]he way to stop discrimination on the basis of race is to stop discriminating on the basis of race" (Parents Involved in Community Schools v. Seattle School Dist. No. 1, 551 U.S. 701, 748 (2007)). Part of their reluctance to support affirmative action is that affirmative action was meant to be temporary (United Steelworkers of America, AFL-CIO-CLC v. Weber, 443 U.S. 193 (1979)). If racial and gender discrimination in academic promotion are waning then the need for the stronger forms of affirmative action may no longer exist.

The current state of the law is not favorable to claims of discrimination in academic promotion. First, judicial deference to academic freedom means that most claims of discrimination in academic promotion by a professor against their department or university are unsuccessful, with the professor losing about 80% of the time (Hora

2001, 356; West 1994, 124-125; White 2010, 842). This is mainly because courts often grant universities great academic freedom as

> [i]t is the business of a university to provide that atmosphere which is most conducive to speculation, experiment and creation. It is an atmosphere in which there prevail 'the four essential freedoms' of a university—to determine for itself on academic grounds who may teach, what may be taught, how it shall be taught, and who may be admitted to study'

(Sweezy v. N.H. by Wyman, 354 U.S. 234, 263 (1957)). This study may provide evidence that will help to decide how much longer affirmative action should continue and whether the scope of academic freedom might be limited a bit so professors can more easily assert their claims of discrimination in academic promotion. If there is obvious evidence that gender or race hinder promotion and this difference is unexplained after correction for the relevant variables, then it would be appropriate to consider: (1) extending and expanding affirmative action; (2) making it easier for professors to assert claims of discrimination in academic promotion; and (3) reducing the scope of academic freedom a bit.

Generally studies which detect no difference between the groups being compared are ignored (Dubben and Beck-Bornholdt 2005, 433). Gender discrimination in academic promotion is different in the sense that either evidence that discrimination persists or is no longer present would be meaningful. Both policy and legal implications would exist with either a positive or a negative result.

Another important issue is where to look for gender discrimination in academic promotion. The distribution of faculty by gender might suggest which institutions are most likely to provide evidence of gender discrimination (see Table 5).

Table 5. Distribution of Male and Female Faculty by Academic Rank and Institutional Type.

Proportion of Males and Women by Academic Rank and Institutional Type

	College 2 Year		College 4 Year		University	
	Males	Females	Males	Females	Males	Females
Full Professor	8%	7%	28%	12%	41%	12%
Associate Professor	16%	15%	28%	25%	26%	20%
Assistant Professor	13%	14%	31%	37%	22%	35%

Proportion of Males and Females by Academic Rank

	1979		1989		1995	
	Males	Females	Males	Females	Males	Females
Full Professor	50%	22%	55%	27%	54%	28%
Associate Professor	31%	32%	27%	36%	28%	35%
Assistant Professor	20%	45%	17%	37%	18%	38%

Gender Difference (%Males - %Females) in Tenure after Correction for Other Variables

	Institutional Type		
Year	Research I	Doctoral	Baccalaureate
1979	20%	13%	20%
1989	13%	6%	3%
1995	13%	10%	4%

Bayer (1973, 23; see top of Table 5) surveyed American faculty in 1972-1973 and presented evidence showing that the proportion of male and female professors was about the same in two-year colleges but grossly different in universities where females lagged males especially with advancing academic rank. Long (2001, 166, 172; see middle and bottom of Table 5) used logistic regression and found that females continued to lag males as professors between 1979 and 1995 despite correction for multiple variables and this was most marked in doctoral institutions. According to Marschke et al. (2007, 4) there is an inverse relationship between proportion of females on the faculty and the prestige of the institution. These studies suggest that gender discrimination is most likely in PhD-granting institutions; these institutions are the focus of this study. In terms of disciplines, one of the less hospitable to females is geography as measured by the proportion of females receiving PhDs, where the fraction of female PhDs is about 24%, a little lower than philosophy at 29% (Bishop, et al. 2013, 247), equal to economics at 24%, and just above mathematics with 21% (Holden 1996, 1919; Long 2001, 37-39). Remember that economics and mathematics are disciplines where some of the best evidence of gender discrimination in academic promotion exists (Ginther and Kahn 2004, 201-203; Kaminski and Geisler 2012, 865-866). Some experienced observers of geography, such as Wilbur Zelinsky, noted:

> If there have been some significant shifts in race relations recently and in the status of some minority groups, areas where noise can be roughly equated with change, such has not yet been the case for the academic woman. Clearly women geographers and their colleagues in other fields have far to go before either their numbers or their professional accomplishments begin to rival those of their masculine associates

(1973, 163). In 2000 Luzzadder-Beach and Macfarlane (421) noted “affirmative action and efforts to counter discrimination need to improve in promotion and retention of female faculty if physical geography is to continue to grow in diversity.” All this suggests that discrimination in academic promotion, if it persists, is most likely to be found in PhD-granting institutions in fields such as geography. If one of the best places to seek gender discrimination in academic promotion is PhD-granting departments of geography, then a study comparing matched cohorts of males and females would be the design providing the most convincing evidence.

The purpose of this study is to evaluate the effect of gender and race on promotion of a cohort of PhDs at academic institutions and at geography PhD-granting institutions. The outcomes of this study will be the proportion of women hired as assistant professors and later promoted to become associate professors, as well as the number of years between granting of a PhD in geography and hiring as an assistant professor, the proportion promoted year by year, and the number of years before promotion to become an associate professor.

3. RESEARCH QUESTIONS

The research questions, stated as null hypotheses, are listed in Table 6.

Table 6. Research Null Hypotheses.

Hypothesis 1:

Independent of race and gender, PhDs in geography will take the same amount of time to be hired as assistant professors or to be promoted to become associate and full professors at PhD-granting academic institutions, after correcting for independent variables, such as number of publications.

Hypothesis 2:

The proportion of assistant professors promoted to become associate and full professors in geography departments at PhD-granting academic institutions is independent of race and gender, after correcting for independent variables, such as number of publications.

Hypothesis 3:

The annual rate of promotion of assistant and associate professors in geography departments at PhD-granting academic institutions is independent of race and gender, after correcting for independent variables, such as number of publications.

Hypothesis 4:

The annual rate of promotion of assistant and associate professors in geography departments at PhD-granting academic institutions is independent of their research focus or sub-discipline.

Hypothesis 5:

The proportion of male and female faculty members at PhD-granting institutions will be the same in all regions of the U.S.
.

For each of these five hypotheses, the null hypothesis, H_0, is that that there are no differences attributable to race or gender (Zar 2010, 78-80). The alternative hypothesis, H_A, is that race and/or gender does alter hiring, promotion, or regional distribution, so two-tailed tests will be conducted with an alpha, or significance level, of 0.05, or 5% (Zar 2010, 78-80). The main research question is does race or gender influence the hiring of a PhD or the promotion of an assistant and associate professor at an academic institution, after controlling for other factors. The variants of this research question concern the time to promotion, the proportion promoted, and the rate of promotion, after correcting for independent variables, at a PhD-granting department of geography in this country. Another research question is whether research focus or academic sub-discipline has any effect on academic promotion. The last research question is whether the proportion of females in geography faculty varies by region of the country.

While the focus of this research is on the effect of gender and race on academic promotion, the actual results of the study may force the consideration of other factors. The process of correcting for the effect of other variables may lead to the identification of factors not previously associated with academic promotion and the analysis will need to be adjusted to reflect these discoveries.

4. METHODS

4. A. Data Collection

Two main sources of data were used in this study: (1) publically available information and (2) data obtained by survey. Publically available information about academic careers is extensive. This study started with Association of American Geographers' *Guides and Directories*, which was used to define which professors were part of geography. This information was supplemented by information available at departmental websites and in university catalogs. There were gaps in publically available information and questionnaire responses were used to attempt to fill these gaps. Generally public information was lacking for more personal variables such as marital status or number of children and questionnaire responses were used to estimate these variables.

The variables used in this study are listed in Table 7.

Table 7. Research Variables and their Definitions.

Demographic Variables
Age and Sex Race: Caucasian, African-American, Asian, Native American, and Other Foreign Born
Employment Variables
Year when PhD granted, hired, and promoted to associate professor and full professor Rank of PhD-granting and assistant professor employing institution with high ranked group: Clark University, Ohio State University, Pennsylvania State University, State University of New York at Buffalo, Syracuse University, University of California-Berkeley, University of California-Los Angeles, University of California-Santa Barbara, University of Colorado, Boulder, University of Minnesota-Twin Cities, University of Wisconsin-Madison, and University of Washington Academic subdiscipline: GIScience, human, physical, and regional Research focus: Geography, Geology, Ecology, Urban Planning, Anthropology, Meteorology, Engineering, Sociology, Economics, Policy, History, and Education Inbreed: appointment as assistant professor at institution granting PhD Main employment activities: hours spent in research, teaching, administration, or other Year of promotion or when awarded tenure Moves while assistant professor: number, PhD-granting, gained promotion by move
Productivity Variables
Number of publications, cumulative starting five years before PhD granted Number of citations, cumulative starting five years before PhD granted Grant support, amount and number of years
Family Variables
Marital status: Legal marriage; committed relationship for more than one year; single which includes widowed, separated, divorced; and never married Dual-career status or whether partner shares similar career status Degree partner works: full-time, part time, or not employed Partner shared academic work at: a university, same university, same department Children and their ages with early baby within five years of after granting of PhD Geographic limitation in job search Voting preferences: Republican Party, Democratic Party, or No Opinion

Table 7. Research Variables and their Definitions (continued).

Regional Variables
Regions: Far West: AK, CA, HI, NV, OR, and WA Great Lakes: IL, IN, MI, OH, and WI New England and Mideast: CT, ME, MA, NH, RI, VT, DE, DC, MD, NJ, NY, and PA Southeast and Southwest: AL, AR, FL, GA, KY, LA, MS, NC, SC, TN, VA, WV, AZ, NM, OK, and TX Plains and Rocky Mountain: IA, KS, MN, MO, NE, ND, SD, CO, ID, MT, UT, and WY

A map of the geographic regions is shown in Figure 1 in the APPENDIX. These variables were suggested by the review of the literature and many determined by responses to a questionnaire.

Responses to a self-administered questionnaire provided information on many of the variables as shown in Table 8.

Table 8. Information Requested in Questionnaire.

Variable	Response
Birth Year	Enter four-digits
Sex	Check Female or Male
Race	Check White; Black or African American; Asian; Hispanic, Latino, or Spanish; Native American; Other
US Birth	Check Yes for born in United States or No
Work Hours	Hours per week spent in teaching, research, administration and other activities
Subdiscipline	Percentage time in GIScience, human geography, physical geography, regional geography and other
Tenure	Check Yes or No and enter year if checked Yes
Tenure Track	Check Yes or No and enter year if checked Yes
Grants	Check Yes or No if have received grant or contract and enter amount and duration
Marital Status	Check Legal marriage, Committed relationship for more than 1 year, Single which includes widowed, separated or divorced or Never married
Spouse Works	Check Full-time, Part-time or Does not work
Site Spouse Work	Check College or university, My college or university, My department or None of above
Children's Birthdays	Check No children or enter birth year of children
Caregiver	Check if primary caregiver to someone other than children
Search Limits	Check No geographic limitations or Where job search limited to and why
Party Vote for	Check Republican, Democratic, or No Opinion

The questionnaire, its associated mailings, and IRB approval for the questionnaire are included in the APPENDIX. The mailings included a pre-notice letter followed four to five days later by a letter including the questionnaire and a token of appreciation, a $2 bill, followed a week later by a thank you postcard, and finally two weeks later a e-mail with an attached fillable PFD questionnaire.

The outline of most academic careers in geography can be found in Association of American Geographers' *Guides and Directories*, which provide lists of faculty ranks and institutional affiliations, which is complete from 1968 to 2012 with incomplete listings back to 1956. Professors were identified between 1991 and 2007 in the *Guides and Directories* and traced in time to complete their academic careers with about 97% to

98% of assistant professors traced until they were promoted. As needed university or college catalogs and departmental websites were used to complete information on when a professor received his or her PhD, started working as an assistant professor, were promoted to associate or full professor. Gender can usually be discerned by departmental photos, pronouns used to describe the faculty member, and the usual gender of his/her first name; this can be validated via questionnaire responses. Gender and other binary variables were coded 0 or 1, for example Female = 1 and Male = 0. Some variables, such as race, were coded as integers. Usually the year when a professor's PhD was granted is available in the Association of American Geographers' listing or within departmental websites, but occasionally Proquest's dissertation and theses database was used to find the year a professor's PhD was granted. The top twelve ranked of PhD-granting and employing institutions in geography were found in National Research Council's 1995 rankings. Publications and citations were found with the Thomas Reuters' Web of Science which included all databases. The focus of the professor's research was identified using information provided by the department granting their PhD as well as their publications and ProQuest Dissertation and Theses subject coding for their dissertation. Inbred status was coded as 1 if the professor started working as an assistant professor at the same institution where they received their PhD and was coded 0 otherwise. Moves while employed as an assistant professor were recorded including the total number of moves, moves to a PhD-granting institution, and moves to gain promotion. Regional variables were integers used to represent where an assistant professor worked. Often more than one public source was available for data which should reduce error in the data.

4. B. Methods

Surveys are prone to four types of error: coverage, sampling, measurement, and non-response (Dillman, Smyth, and Christian 2009, 16-18). Coverage error occurs when "not all members of the population have a known, nonzero chance of being included in the sample." In this study the population of professors is defined by the Association of American Geographers' *Guides and Directories* and cross checked with listings in departmental websites and institutional catalogs. While identification of the population is relatively easy, the matching design of this study may yield a sample that is not be representative of the whole population (Dillman, Smyth, and Christian 2009, 17; Long 2001, 25). Sampling error has to do with how wide the confidence intervals are and varies with sample size and is $< \pm 3\%$ for all samples of 100 or more, which will be true for most variables in this study (Dillman, Smyth, and Christian 2009, 17, 57). Measurement error occurs when questionnaire responses are not accurate (Dillman, Smyth, and Christian 2009, 17). Most of the questions in this survey (see APPENDIX) will call for factual responses where measurement error should be small. This was checked for gender and the result based on photos, name and descriptive pronouns vs. the questionnaire response differed by $< 0.003\%$. Non-response error is where people who do not respond to the survey are different from those which do respond (Dillman, Smyth, and Christian 2009, 17). Those who respond to this survey will be compared with those who do not respond to see if: (1) their demographic and other variables are similar; and (2) questionnaire response can be predicted with logistic regression using variables that are likely to predict promotion. Reducing the percentage of those who do not respond to the questionnaire will tend to reduce non-response error.

Gender discrimination in academic promotion occurs over time, so a longitudinal research design would be favored over a cross-sectional research design. Since the focus of this study is differences between males and females in time to academic promotion, a matched cohort study has the advantage of potentially reducing the effect of extraneous variables due to age-cohort or institutional effects. Age-cohort effects could be reduced by matching males and females using the year the professor's PhD was granted, as have other studies (Ginther 2001, 20; Ginther and Hayes 2003, 50; Long 2001, 160-161). A limitation of matching is that it does not completely separate age and age-cohort effects and also selects a population less representative of the general population (Glenn 2005, 6; Long 2001, 25). This study will focus on geography departments in PhD-granting institutions where males and females were matched by being assistant professors in same PhD-granting department of geography and approximately matched by the year of their PhD was granted. Matching by type of institution, department, and approximate year their PhD was granted will reduce differences in males and females due to unmeasured variables associated with differing institutional types, departments, and years of academic experience (Kleinbaum, Kupper, and Morgenstern 1982, 380-382).

This study followed a matched cohort of assistant professors over time to see whether promotion in geography departments at PhD-granting institutions varies with gender or other variables. Survival analysis was used to compare the time to promotion of females and males; it differs in some ways from the more commonly used multivariate linear and logistic regression. Multivariate linear regression is typically used to detect relationships between a set of k-independent variables, X_1 to X_k, and the dependent variable, Y, with

$$Y = \alpha + \beta_1 X_1 + \ldots + \beta_k X_k, \quad (1)$$

where α and β_1 to β_k are the coefficients (Hair Jr. et al. 2010, 181). With multivariate regression both the dependent and independent variables are real numbers and independent variables can be binary, or limited to being 0 or 1. When the dependent variable is binary, logistic regression is used with

$$ln\left[\frac{p}{1-p}\right] = \alpha + \beta_1 X_1 + \ldots + \beta_k X_k, \quad (2)$$

where p is the probability that an event will occur and varies from 0 to 1 (Hair Jr. et al. 2010, 326). One form of survival analysis is Cox regression where independent variables, which can be real numbers including binary numbers, are used to predict the time to the occurrence of a binary event, such as academic promotion (Hosmer, Lemeshow, and May 2008, 1-2).

When should survival analysis be used instead of logistic or multivariate regression? Survival analysis should be used when censored data is expected (Klein and Moeschberger 2003, 63-72; Kleinbaum and Klein 2005, 4-7). Typically data becomes censored when some members of the cohort are expected to leave before the event used to measure time occurs. If assistant professors were followed to see when they were promoted to become associate professors, then some would be expected to leave without being promoted; this would generate right-censored data. Also, right-censored data could occur if the follow-up period was not long enough to include the event, such as when promotion occurs (Hosmer, Lemeshow, and May 2008, 7). For cohorts of PhDs or assistant professors, right-censored data would be expected, so survival analysis is the appropriate method of analysis.

Survival analysis includes the descriptions of survival curves followed by adjusting the survival curves for independent variables, if needed. Survival curves are described with survival functions, S(t), which is the probability of surviving longer than time t, or not being promoted by a certain number of years, with

$$\mathrm{S(t)} = Pr(\mathrm{T} > t) = \int_{\mathrm{t}}^{\infty} \mathrm{f(x)dx}, \tag{3}$$

where T is a random variable, or the time to promotion, and t is a specific time (Hosmer, Lemeshow, and May 2008, 16; Klein and Moeschberger 2003, 22). The function f(x) is a probability density function of the chance of being promoted in a given year, which is always non-negative and has an area under its curve of one (Klein and Moeschberger 2003, 22). Survival curves are estimated using the product limit, or the Kaplan-Meier, estimator (Hosmer, Lemeshow, and May 2008, 17-26) and then compared using the log-rank test (Kleinbaum and Klein 2005, 57-61). One advantage of Kaplan-Meier is they make no assumptions about the distribution of the T, time to promotion (Selvin 2008, 72-73). A limitation of Kaplan-Meier survival curves is they cannot estimate or adjust for the effect of independent variables or covariates.

The effect of independent variables, or covariates, can be estimated using the Cox proportional hazards model, which is based on the hazard function. The hazard functions, h(t), describe the conditional failure rate over a small increment of time, $\Delta\mathbf{t}$, with

$$\mathrm{h(t)} = lim_{\Delta\mathrm{t} \to 0} \frac{\mathrm{P(t \le T<}t\mathrm{+}\ \Delta t \mid T \ge t)}{\Delta\mathrm{t}}, \tag{5}$$

where $\mathrm{P(t} \le \mathrm{T} < t + \Delta t \mid T \ge t)$is the conditional probability that a subject's failure time, T, will lie in the interval between t and t + $\Delta\mathbf{t}$, given that the subject has survived to time t (Kleinbaum and Klein 2005, 11). The hazard function is called the conditional failure rate, as it gives the probability per unit time of the selected event occurring and can vary from zero to infinity (Klein and Moeschberger 2003, 27; Kleinbaum and Klein 2005, 11). The hazard function, h(t), and the survival function, S(t), are related with

$$h(t) = -\frac{\frac{dS(t)}{dt}}{S(t)} \tag{6}$$

and

$$S(t) = \exp\left[-\int_0^t h(u)du\right] \tag{7}$$

(Kleinbaum and Klein 2005, 14). Once the hazard function is known, the survival function can be determined and the reverse. Independent variables are added in the Cox proportional hazards model by modifying the hazard function so that it becomes

$$h(t, X) = h_0(t)e^{\sum_{i=1}^{k} \beta_i X_i}, \tag{8}$$

where $h_0(t)$ is the baseline hazard function, β_i are the coefficients, and X is the array of X_i independent variables (Klein and Moeschberger 2003, 243-245; Kleinbaum and Klein 2005, 94). The Cox proportional hazards model leaves the baseline hazard function, $h_0(t)$, unspecified and the independent variables, X_i, can be fixed or vary over time. It may be useful to estimate the baseline cumulative hazard function in a Cox model, H(t|x) as

$$H(t|x) = \int_0^t h(u|x)du = exp(\beta_k x_k)\int_0^t h_o\ (u)du = \exp\,(\beta_k x_k)H_0(t) \tag{9}$$

(Cleves et al. 2010, 135-138). Once the hazard function is known then the survival function can be calculated using equation (7). The estimated hazard ratio, $\widehat{HR}$, is the ratio of two estimated hazard functions or

$$\widehat{HR} = \frac{\hat{h}_{0_A}(t)e^{\sum_{i=1}^{k}(\beta_i X_i)}}{\hat{h}_{0_B}(t)e^{\sum_{i=1}^{k}(\beta_i X_i)}} = exp\left(\sum_{i=1}^{k} \beta_i [X_{iA} - X_{iB}]\right), \tag{10}$$

where X_{iA} are the k-independent variables for one group and X_{iB} are the k-independent variables for the other group (Klein and Moeschberger 2003, 243-245; Kleinbaum and Klein 2005, 100-101). The hazard ratio is a measure of the size of the effect and can be calculated for each β_i coefficient (Kleinbaum and Klein 2005, 100-103). The maximum likelihood method is used to estimate the β_ι coefficients and then the Wald test can be used to evaluate their significance (Hosmer, Lemeshow, and May 2008, 134; Kleinbaum and Klein 2005, 98-100). Maximum likelihood estimation assumes that there are not an excessive number of tied survival times (Hosmer, Lemeshow, and May 2008, 85-87; Klein and Moeschberger 2003, 259-263). The significance of tied survival times will be evaluated using the Breslow and exact partial likelihood approximations (Hosmer, Lemeshow, and May 2008, 85-87; Klein and Moeschberger 2003, 259-263). The advantage of survival analysis is that it is designed explicitly for censored data and makes use of all available data.

Selection of variables started by ranking the variables by their univariate p-value (Hosmer, Lemeshow, and May 2008, 133). The univariate p-value was calculated using Cox proportional hazards regression and estimating the significance of the variable's coefficient with the Wald test (Hosmer, Lemeshow, and May 2008, 133-134). The variables were ranked according to their p-values with the smallest atop the list and including variables with p-values down to cutoff value (Hosmer, Lemeshow, and May 2008, 133).

Each of the variables ranked by their univariate p-values was examined to see how many events or observations were available for that variable. With binary variables events were only available for some professors. For example, relatively few professors were inbred, or hired as assistant professors by the same institution that granted their

PhD. Next, the event-per-variable ratio was calculated for each variable included in the model (Hosmer, Lemeshow, and May 2008, 136; Royston and Sauerbrei 2008, 47). Last, a rule of thumb was used for how many events-per-variable should be present with the typical suggestion of a lower limit of ten events for each variable with more, 15:1 to 25:1, being desirable (Hair et al. 2010, 176; Hosmer, Lemeshow and May 2008, 136; Royston and Sauerbrei 2008, 47). Reducing the event-to-variable ratio increases the risk that the coefficient estimate will be in error especially for weak predictors (Royston and Sauerbrei 2008, 47-48; Vittinghoff and McCulloch 2007, 717).

Studies of academic promotion have examined a large number of variables, but only a few of the variables have highly significant p-values; these strong predictors can be defined by the coefficient having a p-value < 0.001 (Royston and Sauerbrei 2008, 30). Many of the remaining variables have p-values associated with their coefficients of > 0.05; these are weak predictors (Royston and Sauerbrei 2008, 30). A limitation of use of data-driven methods to select variables for inclusion in a regression model is that they typically correctly identify strong predictors but are often biased in their selection of weak predictors (Miller 2002, 165; Royston and Sauerbrei 2008, 40, 48). Why does bias occur in the selection of weak predictors? A given sample might yield an estimate of a variable's coefficient which was little larger or smaller than the true value. A minor change in the magnitude of a variable's coefficient would have less effect with a strong predictor, where the ratio of the coefficient to its standard error is large, than with a weak predictor, where the ratio of the coefficient to its standard error is smaller and near the ratio signifying statistical significance (Royston and Sauerbrei 2008, 40). Thus, minor errors in the estimation of the magnitude of a coefficient could lead to the inclusion of a weak predictor but would be less likely to lead to the exclusion of a strong predictor (Royston and Sauerbrei 2008, 40). What to do about the problem of the inclusion of weak predictors in a multivariate regression model? First, make sure that the sample size is adequate using the events-per-variable criterion (Hair et al. 2010, 176; Hosmer, Lemeshow and May 2008, 136; Royston and Sauerbrei 2008, 47). Next, the goal should be to identify strong predictors where variable selection bias is less likely (Royston and Sauerbrei 2008, 40).

Given the large number of variables, about 30 reviewed in Table 2, that have been used in studies of gender discrimination on academic promotion, how many are strong predictors or have p-value being consistently < 0.001? Table 9 in the APPENDIX reviews studies which report variables with significant p-values. As Table 9 in the APPENDIX shows no coefficients have been consistently shown to p-values less than 0.001 and only 11 variables have any studies reporting a p-value < 0.001. Eight variables have at least two studies showing a coefficient with a p-value < .01. Thus, the literature suggests only a handful of variables are likely to be highly significant. This suggests that regression models may only need to include a small number of variables to identify the strong predictors of academic promotion.

Generally the main goal of variable selection is either prediction or explanation (Royston and Sauerbrei 2008, 26-29). If the main goal is prediction, then the inclusion of all weak predictors, even those of marginal significance would be appropriate (Royston and Sauerbrei 2008, 26-29). Unfortunately the inclusion of weak predictors is likely to lead to models which are complex, difficult to interpret, and less likely to transfer to other similar data sets (Royston and Sauerbrei 2008, 48-50). If the main goal is explanation, then the loss of some weak predictors is acceptable as explanation if favored by creating a simpler, easier to interpret, and more reproducible regression model (Royston and Sauerbrei 2008, 26-29, 48-50). Studies of gender discrimination in academic promotion, including this study, have a main goal of identifying variables which explain promotion (Royston and Sauerbrei 2008, 26-29). The consequence of favoring explanation is the acceptance of the loss of some weak predictors where selection bias is most likely (Royston and Sauerbrei 2008, 26-29).

The tradeoff between simple and complex models was demonstrated by varying the p-value cutoff point to create models varying in complexity. A low p-value cutoff created a Cox regression model with few variables; this can be compared with Cox regression models containing more variables where the cutoff p-value was higher. The smaller and larger Cox regression models were compared to see if the strong predictors are consistently identified as well as whether weaker predictors were consistently included in the Cox regression model. Before the strength of a predictor within a model was evaluated a method to perform Cox regression was needed.

Once the variables were ranked by p-values, the next step was to transform the data as needed so that the variable is has a linear log hazard and fit a multivariate Cox regression model using backward elimination where all the variables are included in the model and then eliminated one-by-one depending on their contribution to the model (Hosmer, Lemeshow and May 2008, 136, 162-163; Royston and Sauerbrei 2008, 117-120). The program used is Stata's multivariable fractional-polynomial models with Cox regression selected. The automated multivariate model building program uses fractional polynomials and combines backward elimination and a functional selection procedure to transform the data as needed (Royston and Sauerbrei 2008, 117-120). The transform selected is initially linear, where the power is 1, but can be changed to include multiple powers or a log transform, which is defined as a power of 0. The powers evaluated are: -2, -1, -1/2, 0 (ln), ½, 1, 2, 3; the transform can include products of terms, such as xln(x). Categorical or binary variables are not transformed, but other variables are transformed as needed so that they are linear in the log hazard function (Hosmer, Lemeshow, and May, 2008, 162-163). Taking the log of the hazard function, shown in equation (8), and then taking the partial derivative with respect to a given variable, Xi, gives

$$\frac{\partial ln[h(t,X)]}{\partial X_i} = \frac{\partial ln[h_0(t)]}{\partial X_i} + \frac{\partial}{\partial X_i}\left[\sum_{i=1}^{k}(\beta_i X_i)\right] = \beta_i \qquad (11)$$

which shows that the coefficient β_i is expected to be partial derivative of the log hazard function with respect to a given variable. The backward elimination algorithm initiates cycles where it examines: (1) variables for possible elimination; (2) retained variables to see if they are linear in the log hazard function; and (3) the transform of one variable to see if it changes the scaling of another variable (Hosmer, Lemeshow, and May, 2008, 163). The algorithm ends when the results of two cycles are the same; then it displays the transforms used for each variable and the variables selected to be include in the model (Hosmer, Lemeshow, and May, 2008, 163). Next, interaction terms are considered for inclusion in the model (Hosmer, Lemeshow, and May, 2008, 134-135). The interaction of gender with other variables included in the Cox regression model will be evaluated by calculating gender specific coefficients for each variable.

This study matched cohorts of male and female professors based on: (1) being an assistant professor at the same institution and (2) the year their PhDs were granted; this can be viewed as two stratified cohorts where institution and year of PhD are held approximately constant in a matched cohort design (Hosmer, Lemeshow, and May, 2008, 208-213; Klein and Moeschberger 2003, 311). To assess the effect of the matching variables (institution, year of PhD awarding, and gender) a stratified Cox proportional hazards model will be fit (Hosmer, Lemeshow, and May, 2008, 208-213; Kleinbaum and Klein 2005, 176-194). The stratified Cox proportional hazards model accommodates stratifying variables which are, or can become, categorical; these variables do not have to satisfy the proportional hazards assumption (Hosmer, Lemeshow, and May, 2008, 208; Kleinbaum and Klein 2005, 176). Of the stratifying variables, gender is categorical, but institution and year PhD was awarded will need to be converted into categorical variables. Institutions can be divided into top-ranked institutions vs. other institutions and the year a professor's PhD was awarded will be divided into three approximately equal groups by selecting years, say 1989 and 1997, which divides the professors into three approximately equal groups. A limitation of using a stratified Cox regression model is that potential stratifying variables, such as gender, cannot be included within the regression model. To minimize the loss of variables to stratification, Kaplan-Meier survival curves were compared for these potentially stratifying variables: (1) gender; (2) employment at a top-ranked program; and (3) cohort of PhDs granted before 1989, between 1989 and 1997 and after 1997. Only variables whose Kaplan-Meier survival curves crossed were used to stratify the Cox regression model. While coefficients are lacking for stratifying variables, it is possible to calculate gender specific coefficients for other variables (Kleinbaum and Klein 2005, 179).

The adequacy of the Cox regression model will be evaluated by checking to see if: (1) the proportional hazards assumption is met (Hosmer, Lemeshow, and May 2008, 177-

184); (2) any values of the variables might unduly influence the estimate of the variable coefficients (Hosmer, Lemeshow, and May, 2008, 184-191; Klein and Moeschberger, 2003, 385-391); and (3) the overall fit of the model is adequate (Hosmer, Lemeshow, and May, 2008, 175-177). The proportional hazards assumption is that the estimated hazard rate, $\widehat{\mathrm{HR}}$, is constant over time (Klein and Moeschberger 2003, 243-245). The validity of this assumption will be assessed by: (1) examining plots of –ln[-ln(S(t))] vs. ln(Time) to see if they are approximately linear (Kleinbaum and Klein 2005, 137-141); (2) examining plots comparing Kaplan-Meier survival curves with survival curves generated by Cox regression adjusted using the mean values of their covariates; and (3) showing that the smoothed scaled Schoenfeld residuals are not related to survival time (Hosmer, Lemeshow, and May 2008, 177-184; Kleinbaum and Klein 2005, 151-153). Next, the model was checked for professors which the model did not fit well and whose extreme values might unduly influence the coefficients of the model. This was done by plotting Stata's efficient score residuals for each variable and examining the plot for unusual values (Hosmer, Lemeshow, and May, 2008, 139, 184-188). As unusual values were detected the database was checked to see if there were any data-entry errors to be corrected and to see if the values were plausible. The overall fit of the model was evaluated by plotting Cox-Snell residuals vs. the cumulative baseline hazard to see if the slope is one and the intercept is zero (Box-Steffensmeier and Jones 2011, 120; Klein and Moeschberger 2003, 354-359; Tableman and Kim. 2004, 168-169).

Survival curves will be estimated by both Kaplan-Meier product-limit estimation and mean adjusted Cox regression models. Kaplan-Meir survival curves are nonparametric in that their calculation makes no assumption about an underlying distribution of survival times (Selvin 2008, 72-73). Cox regression models can be used to estimate survival curves after adjusting the curves for the mean value of all the covariates save gender which is coded 0 for male and 1 for female professors as suggested above in equations (7) and (9); Cox regression models assume that the baseline hazard functions for males and females are proportional. Estimated survival curves for males and females using both Kaplan-Meier and mean adjusted Cox regression can be displayed on the same graph and compared. This is one check for the Cox regression model proportional hazards assumption, but also permits a visual estimation of the effect of variables on the survival curves for males and females.

The relative influence of each variable can be estimated by its calculated hazard ratios using the coefficients estimated by Cox regression and the mean value of each covariate for males and females. Gender specific coefficients will be calculated and used only if they are statistically significantly different. The estimated hazard ratio for the mean of variable X_i, $\widehat{HR}_{\bar{X}_i}$, is

$$\widehat{HR}_{\bar{X}_i} = \exp\left[\beta_{X_i}(\bar{X}_{iF} - \bar{X}_{iM})\right], \tag{12}$$

where $\bar{X}_{iF}$ and $\bar{X}_{iM}$ are the means of the X_i variable for females and males and β_{X_i} is the coefficient for the Xi^{th} variable. The hazard ratio is the ratio of the instantaneous conditional rate of promotion for males and females assuming that they have not already been promoted; it will often be called the rate of promotion. Once the ratios have been calculated for each variable in the Cox regression model, the variables can be organized into meaningful groups, such as productivity variables, and a hazard ratio for productivity variables can be calculated.

The statistical analysis used in this study involved a large number of comparisons. A number of corrections have been suggested including those of Bonferroni and Sidak, among others (Meyers, Gamst, and Guarino 2006, 427-429), but are not routinely used in the literature. This convention will be used in this study. It is tempting to assume statistical evidence of an association or correlation imply causality but this is not the case in this study as it was impossible to conduct an actual experiment.

5. RESULTS

5. A. Evaluation of Questionnaire Response

Questionnaires were sent to 869 professors with the response rates shown in Table 10.

Table 10. Questionnaire Response Rate for Males and Females.

Response	Male	Female	Total
Yes	53.1% (283)	53.7% (180)	53.3% (463)
No	46.9% (250)	46.4% (156)	46.7% (406)
TOTAL	100% (533)	100% (336)	100% (869)

A little over 53% of the professors responded to the questionnaire with no difference in the response rate for males and females (χ^2 = 0.0187, df = 1, p = 0.891). Table 11 and Figure 2 in the APPENDDIX show a breakdown of the questionnaire response by region with no difference between regions detected (χ^2 = 0.0187, df = 4, p = 0.195).

Table 11. Questionnaire Response by Region of the United States

	Questionnaire Response		
Region	Present	Absent	Total
South	56.1% (156)	43.9% (122)	100% (278)
West	51.2% (88)	48.8% (84)	100% (172)
New England	51.8%(101)	48.2% (94)	100% (195)
Lakes	56.0% (75)	44.0% (59)	100% (134)
Plains	50.6% (44)	49.4% (43)	100% (87)
Total	100% (460)	100% (406)	100% (866)

Almost half of the professors failed to respond to the questionnaire, which raises the question of non-response bias.

Since this study focuses on academic promotion it would be important to know that professors responding to the questionnaire were similar to those not responding to the questionnaire in productivity and variables related to promotion as shown in Table 12 in the APPENDIX. Often these variables were skewed so statistical tests included both the t-test and the Wilcoxson rank-sum test. None of these statistical comparisons were significant, although the cumulative number of citations before being promoted to become an associate professor approached statistical significance.

Another way to estimate non-response bias is to see if professors responding to the questionnaire are similar to those not responding to the questionnaire in terms of research focus as show in Table 12 in the APPENDIX. Generally the difference in the research focus of professors responding vs. not responding to the questionnaire was less than about 5% and most differences less than about 1%; no significant difference was detected between the research focus of those responding or not responding to the questionnaire (χ^2 = 10.4, df = 11, p = 0.495).

Non-response bias might be regional, so a comparison the regional distribution of questionnaire response and non-response as shown in Table 12 in the APPENDIX. As shown in Table 11 in the APPENDIX the regional response rate is about the same in those returning their questionnaire and those who do not return their questionnaire with most differences being less than 4%. Overall the differences are not statistically significant (χ^2 = 2.97, df = 4, and p = 0.564).

An overall check for non-response bias would be to use logistic regression to see if any of the variables associated with academic promotion predict questionnaire response, as shown in Table 13.

Table 13. Predict Response with Logistic Regression Using Promotion Variables.

Logistic regression		Number of obs =	485
		LR chi2(16) =	19.45
		Prob > chi2 =	0.2459
Log likelihood =	-324.542	Pseudo R2 =	0.0291

Variable	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
Gender	0.00446	0.204765	0.02	0.983	-0.396872	0.405792
YrPhD	0.005644	0.013673	0.41	0.680	-0.021155	0.032442
TopPhD	-0.19376	0.210748	-0.92	0.358	-0.606816	0.219303
HirePubs	-0.00776	0.058345	-0.13	0.894	-0.122117	0.106593
HireCites	0.002613	0.00156	1.67	0.094	-0.000445	0.005671
AscPPubs	-0.0116	0.017283	-0.67	0.502	-0.045473	0.022276
CiteAscP	-0.00035	0.000447	-0.78	0.433	-0.001225	0.000525
ProfPubs	0.011114	0.009903	1.12	0.262	-0.008296	0.030524
CitProf	-0.00011	0.00022	-0.52	0.606	-0.000546	0.000318
PhDHire	0.041823	0.018774	2.23	0.026	0.0050269	0.078618
Geography	0.414089	0.212066	1.95	0.051	-0.001554	0.829731
MovePhD	-0.43117	0.272251	-1.58	0.113	-0.964775	0.102429
NumMoves	0.271564	0.247023	1.1	0.272	-0.212591	0.75572
New Eng	-0.03288	0.279369	-0.12	0.906	-0.580433	0.514674
South	0.157079	0.270478	0.58	0.561	-0.373048	0.687206
West	-0.18265	0.278236	-0.66	0.512	-0.727985	0.362679
Const	0.130732	0.249626	0.52	0.600	-0.358527	0.619991

Deviance: 649.083.

Overall the regression model was not significant with a p-value of about 0.25. The results show that variables associated with academic promotion are not good predictors of whether a professor will respond to a questionnaire. Thus, the average values of the variables used to predict promotion were not statistically significantly different in those responding to the questionnaire and in those not responding to the questionnaire, nor can these variables be used to predict questionnaire response or its absence. These results encourage the use of questionnaire data along with data from other sources.

5. B. Variable Description

Matched cohorts of male and female professors were selected creating a sample of 336 females and 533 males for a total of 869 professors from 74 institutions, which are listed in Table 14 of the APPENDIX. For every four females nearly seven males were included in the sample giving an average ratio of males to females in these 74 institutions of 1.72 with a 95% confidence interval (95% CI) of about 1.6 to 1.9. As measured by the year that their PhD was granted, males received their PhD about 1.5 years before females with a 95% confidence interval of about 0.6 to 2.4 years. The proportion of women in the total population of professors surveyed was 38% out of a total of 1287 and 39% in the matched cohort; this difference was not statistically significant ($z = 0.35$, $p = 0.73$). Generally the matched samples from the 74 institutions were similar in the ratio of males to females and years that their PhDs were granted and would be expected to be similar in other variables used in this study.

Matching would be expected to yield male and female professors with similar traits and this was usually true when the professor's research focus was compared (see Table 15).

Table 15. Research Focus for Male and Female Professors.

Research Focus	Males	Females	|Difference|
Geography	59.6% (318)*	59.5% (200)	0.1%
Geology	8.2% (44)	5.6% (19)	2.6%
Ecology	7.1% (38)	4.5% (15)	2.7%
Urban Planning	3.8% (20)	7.1% (24)	3.4%
Anthropology	1.9% (10)	8.3% (28)	6.5%
Meteorology	5.3% (28)	3.9% (13)	1.4%
Engineering	5.3% (28)	2.1% (7)	3.2%
Sociology	3.0% (16)	3.6% (12)	0.6%
Economics	2.6% (14)	3.0% (10)	0.4%
Policy	1.5% (8)	1.5% (5)	0.0%
History	1.3% (7)	0.3% (1)	1.0%
Education	0.4% (2)	0.6% (2)	0.2%
TOTAL	100% (533)	100% (336)	

*Number of professors shown in parenthesis.
|Difference| is the absolute value of the difference.

Table 15 shows the surprising variability of the research focus within departments of geography listed in the Association of American Geographers' *Guide to Geography Programs*. Most differences between males and females in their research focus were less than about 3% with the exception of anthropology. The number of professors in each group was compared using chi-square and the difference was significant (χ^2 = 37.3, df = n – 1 = 11, p < 0.0005). Once anthropology was excluded the difference is no longer statistically significant (χ^2 = 17.7, df = n – 1 = 10, p = 0.058). Thus, matching gives groups of males and females sharing similar research interests.

The matched cohorts were also similar in demographic variables as shown in Table 16 in the APPENDIX where significant differences are shown in bold. Females were almost a year older than males, a difference which approached statistical significance. Otherwise, male and female professors were similar in racial mix, regional distribution, and frequency of birth in the US; none of these differences were statistically significant. Maps of the regional distribution by gender and race are shown in Figures 3 and 4 in the APPENDIX. The answer to the fifth research question is that there is no regional difference in the distribution of males and females. Overall demographic variables, except age, were closely matched.

Females are a little older and received their PhD about a year after males received their PhDs (see Table 16 in the APPENDIX). The distribution of the year a professor received his or her PhD is skewed toward large values (Zar 2010, 126) and so the results for males and females were compared with the Wilcoxon rank sum test where the difference was statistically significant (Daniel 1990, 90-96; Zar 2010, 172-174). In addition to a significant difference in age, a greater proportion of females received their PhDs more recently and from top-ranked programs, but males and females did not differ in the proportion working at a top-ranked program or in the years between when their PhD was granted and when they were hired as an assistant professor. Females spent fewer total hours working each week, less time in research, and more time in other activities; males spent more time in research. Females took about 4.8 months longer to be promoted to associate professor, a difference lacking statistical significance, but took a statistically significant 1.2 years longer to reach the rank of full professor. The answer to the first research question is that females take longer to be promoted, but did not differ in time taken to be hired. Male and female professors did not differ in their tendency to move. In terms of specialization males were much more likely to choose GIScience and physical geography; females favored other specializations. Given males spent more time in research it would be expected that they would publish more than females.

Males published more than females and received more citations as shown in Table 16 in the APPENDIX. Although a t-test detects significant difference between male and female professors, the distributions of publications and citations are skewed toward large values (Zar 2010, 126) and so they were also compared by the Wilcoxon rank sum test, which confirm the differences (Daniel 1990, 90-96; Zar 2010, 172-174). Males tended to receive more total funding, more years of funding, and more funding per year than females, but the only statistically significant difference was for the number of years of funding.

Females were less likely to be married, more likely to be single, and more likely to have a working spouse (or partner) than men; males were more likely to have spouses (or partners) that work part time or not at all (see Table 16 in the APPENDIX). In this study, a legal marriage and being single; which includes widowed, separated, or divorced; were separated from a committed relationship lasting for > 1 year; called a partner in Table 16 in the APPENDIX. Over 15% of spouses or partners worked at a university. Females were more likely to work in the same department as their spouse or partner, although this difference was not statistically significant.

Males and females were equally likely to report having children (see Table 16 in the APPENDIX). Further, male and female professors were equally likely to have: (1) “early” babies, or children born within five years after the professor’s PhD was granted; (2) young children, under the age of six years; and (3) older children, between the ages of 6 and 18. Females were more likely to be caregivers, although this difference was not statistically significant.

Females were more likely than males to have their job search limited geographically as shown in Table 16 in the APPENDIX. Over 70% of professors favor the Democratic Party: a preference shared by more females than males. Males are more likely to have no preference in voting than females.

5. C. Kaplan-Meier Survival Curves and Cox Regression Models

Cox regression was used to estimate univariate coefficients for each variable for both associate and full professors. Table 17 lists some of the variable names that will be used in Cox regression models.

Table 17. Variable Names Used in Cox Regression Models.

Abbreviation	Description
Admin	Hours per week spent in administrative work
Amount	Amount in dollars of contract or grant funding
AscPCites	Cumulative citations when promoted to become associate professor
AscPPubs	Cumulative publications when promoted to become associate professor
Demo	Usually vote for Democratic Party
Full	Spouse or partner works full-time
Geog	Research focus in geography
HireCites	Cumulative citations when hired as an assistant professor
HirePubs	Cumulative publications when hired as an assistant professor
Human	Percentage of time spent on human geography
MovePhD	Move as assistant professor to PhD-granting institution
NumMoves	Number of moves as an assistant professor
Other (%)	Percentage of time spent other subdisciplines
PhD<89	PhD granted before 1989
PhD89 97	PhD granted between 1989 and 1997
PhD>97	PhD granted after 1997
PhDHire	Years between granting of PhD and hiring as an assistant professor
Phys	Percentage of time spent on physical geography
ProfCite	Cumulative citations when promoted to become a full professor
White	White or Caucasian race
Years	Years of contract or grant funding

The p-values for each coefficient were ranked with the smallest values at the top. For each coefficient the following were calculated: (1) the total number of professors, (2) number of professors with the event, (3) the univariate p-value, and (4) the smallest events per variable ratio for the largest Cox regression model calculated (Hosmer, Lemeshow and May 2008, 133-136, 141; Royston and Sauerbrei 2008, 47; see Table 18 in the APPENDIX). Only the smallest events-per-variable ratios are shown in Table 18 in the APPENDIX; an event is where the professor has the trait identified by the variable, such as being legally married. Using an events-per-variable ratio of at least 10 yields Cox regression models of about 8 to 15 variables; this is similar to the 12 variables used by Long, Allison, and McGinnis (1993, 711) and the 16 variables used by Ginther and Kahn (2004, 205).

It is not surprising that publications are a strong predictor of academic promotion (Astin and Bayer 1972, 106-108; Ferber and Green 1982, 563; Ginther and Hayes 2003, 52; Ginther and Kahn 2004, 202; Ginther and Kahn 2006, 37; Hesli, Lee, and Mitchell 2012, 480-482; Long, Allison, and McGinnis 1993, 711; McElrath 1992, 275). That HirePubs, or cumulative publications at the time an assistant professor is hired, is a strong predictor of both associate professor and full professor promotion is interesting.

The strength of PhDHire, or years between the awarding of a professor's PhD and when they were hired as an assistant professor, as a predictor of academic promotion was a surprise as only two studies report its negative effect on promotion (Ginther and Hayes 2003, 50; Long, Allison, and McGinnis 1993, 711). Stata's fractional polynomial algorithm used PhDHire to predict the number of years it took for an associate professor to be promoted, or AscPYrs with the results shown in Table 19 and Figure 5.

Table 19. Fractional Polynomial Transform and Linear Regression: PhDHire vs. AscPYrs.

Final multivariable fractional polynomial model for AscPYrs

Variable	-------------Initial----------------			----------------Final----------------		
	df	Select	Alpha	Status	df	Powers
PhDHire	4	1	0.05	in	4	0.5 2

Source	SS	df	MS		
				Number obs =	848
Model	1729.512	2	864.7559	F(2, 845) =	112.73
Residual	6481.893	845	7.670879	Prob > F =	< 0.00005
				R-squared =	0.2106
				Adj R-squared = 0.2088	

AscPYrs	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
PhDHire(1)	16.27852	1.265872	12.86	<0.0005	13.7939	18.76314
PhDHire(2)	-1.37879	0.152703	-9.03	<0.0005	-1.67851	-1.07907
Constant	8.892012	0.111826	79.52	<0.0005	8.672523	9.111502

Deviance: 4131.256.

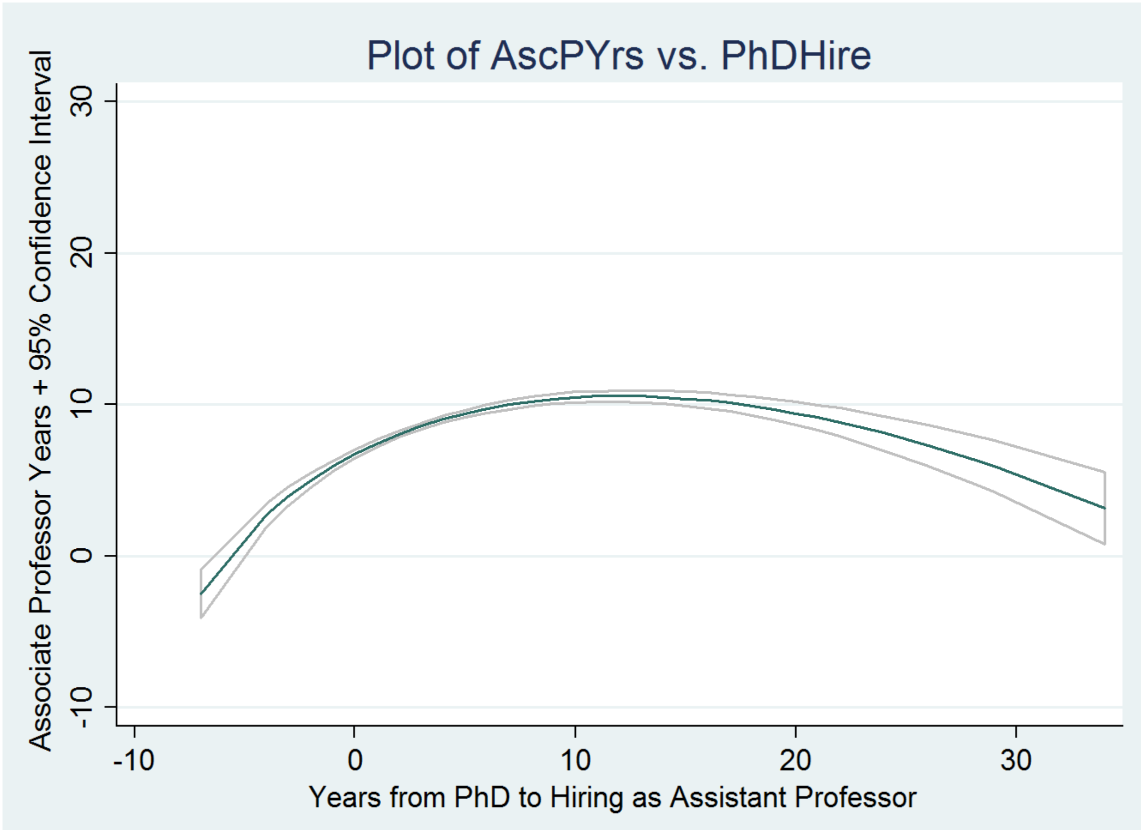

Figure 5. Plot of associate professor years vs. years from PhD to promotion as an associate professor. Solid line is equation which relates AscPYrs (years between PhD-granting and promotion as associate professor) to PhDHire (years between PhD-granting and hiring as an assistant professor) with the 95% confidence interval shown.

The fractional polynomial transform is the sum of

PhDHire(1) = X^0.5 – 1.087 and

PhDHire(2) = X^2 – 1.396, where

X = (PhDHire + 8)/10,

which produces a curve with a 95% confidence interval as shown in Figure 5. The solid line in Figure 5 is the fitted function (Royston and Sauerbrei 2007, 4251; Royston and Sauerbrei 2008, 121). The fractional polynomial algorithm both transforms the data and fits a regression model. This functional relationship shows that the effect of PhDHire should speed promotion: (1) as it becomes more negative and (2) as it becomes larger than about 15 years. Professors who are hired before they are awarded their PhDs are promoted rapidly, taking on average less than 6 years vs. professors hired at the time of their PhD or later, who take over 8 years (t = 6.64, df = 867, p < 0.00005; distribution skewed, Wilcoxon rank sum test, z = 10.123, p < 0.00005). Professors who were hired more than 15 years after their PhD was granted also are promoted a bit faster, 8.2 years vs. 8.9 years, although this difference is not statistically significant (t = 1.17, df = 846, p = 0.242; distribution skewed, Wilcoxon rank sum test, z = 0.469, p = 0.639). This analysis suggests that PhDHire might be a good, if complex, predictor of academic promotion.

White race has a univariate p-value of 0.013 in the prediction of promotion to full professor, which was unexpected. The racial breakdown of professors is: white 81.5%, black 2.6%, Asian 11.1%, and other 4.8%. Whites and blacks are a bit slower and Asians and Hispanics are a bit faster to be promoted to become full professors, although these differences are not significant (see Table 20).

Table 20. Years to Promotion as Full Professor by Race.

	White	Black	Asian	Hispanic	Other
Mean	15.78899	15.85714	13.90323	14	10.5
SD	4.831871	3.716117	3.249152	4.219005	3.535534
N	218	7	31	11	2

Analysis of variance: F = 2.01, df = 2 and 264, p = 0.0931.

Thus, the white race variable identifies a group which is slower to be promoted to become a full professor, although this difference does not reach statistical significance.

Stata's multivariable fractional-polynomial algorithm with Cox regression selected was used to transform the variables as needed and fit a Cox regression model

(Hosmer, Lemeshow, and May, 2008, 163). An example is the transform of the AscPPubs variable,

$$AscP(1) = AscPPubs - 12.91952663,$$

where AscPPubs is the cumulative number publications when the professor was promoted to become an associate professor. A plot of AscP is shown in Figure 6.

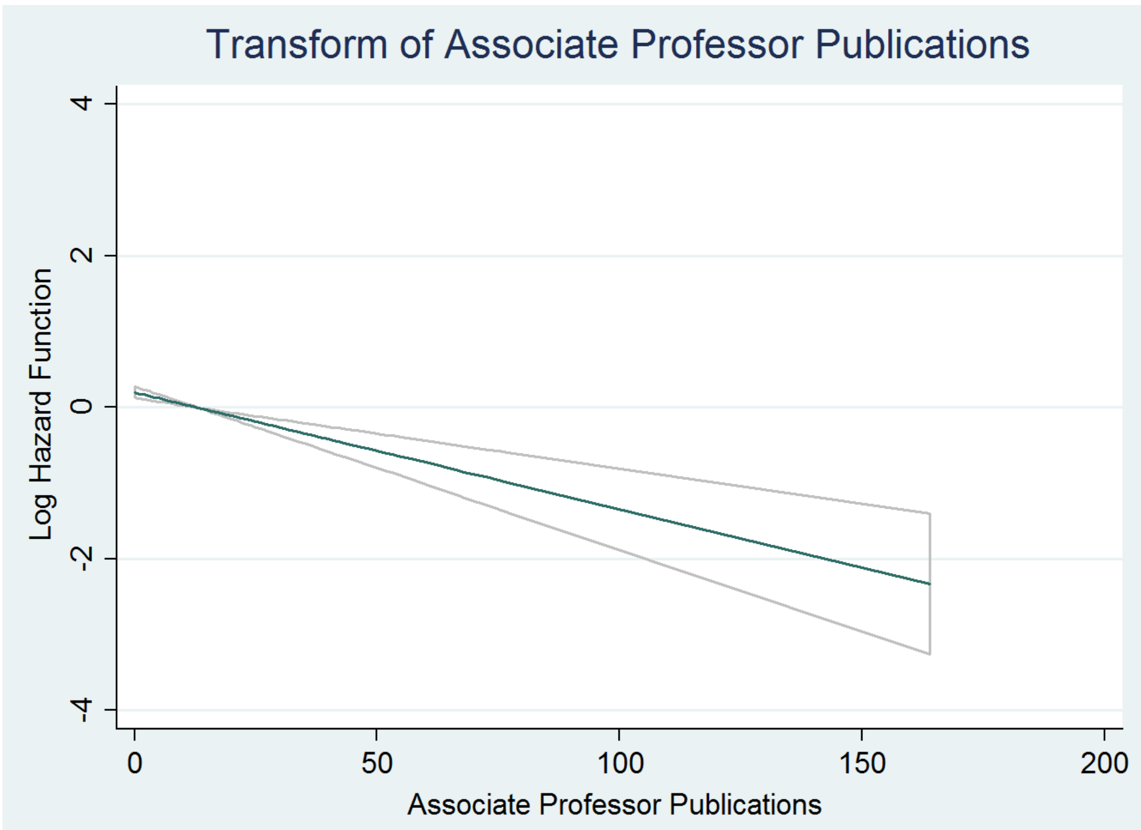

Figure 6. Plot of the log hazard function vs. associate professor publications. Solid line is fitted linear function and 95% confidence interval is shown.

The transform of cumulative publications when promoted to become an associate professor, AscPPubs, is linear with the slope equaling the value of the coefficient of AscPPubs variable (Royston and Sauerbrei 2008, 121); the negative slope means that increasing the number of publications reduces the rate of promotion. Most of the transforms are linear, but some are more complex as used for PhDHire, which is the number of years between when a professor was awarded their PhD and when the professor was hired as an assistant professor (see Figure 7 top)

Top

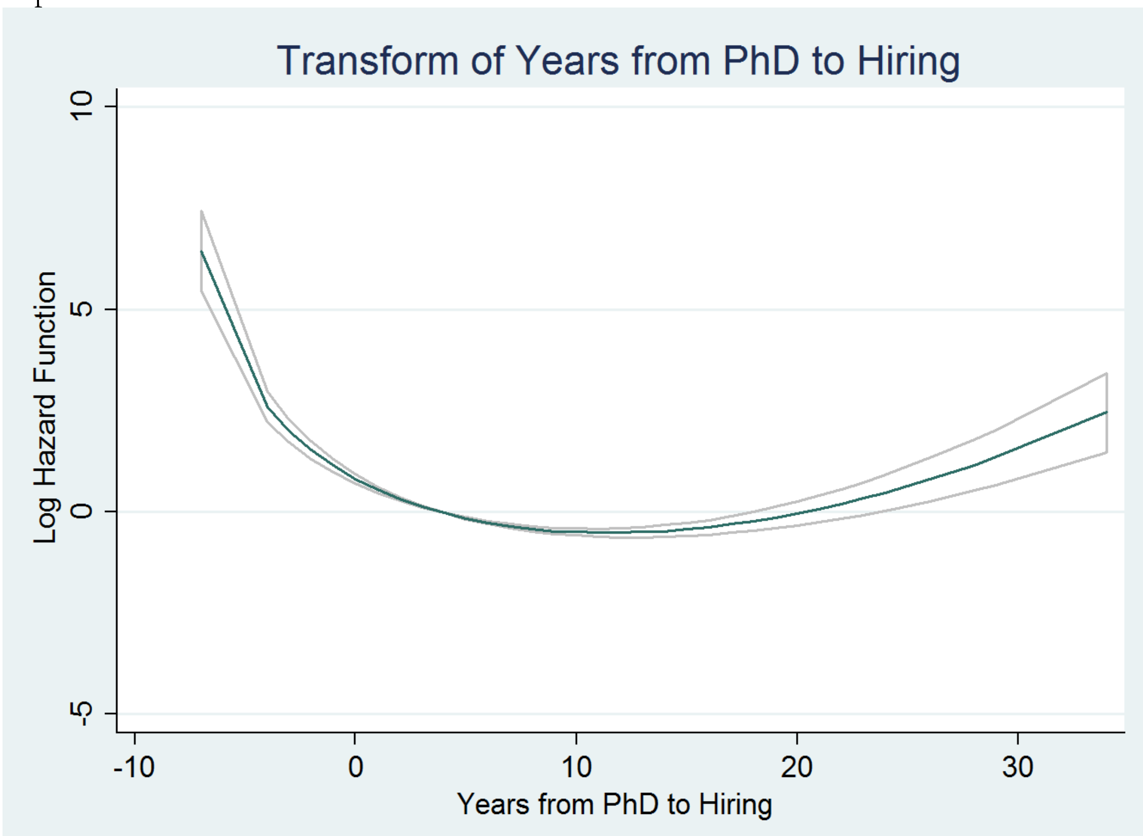

Figure 7. Top. Plot of log hazard function vs. years between PhD-granting and hiring as an assistant professor. Solid line represents fitted function and 95% confidence interval is shown.

Bottom

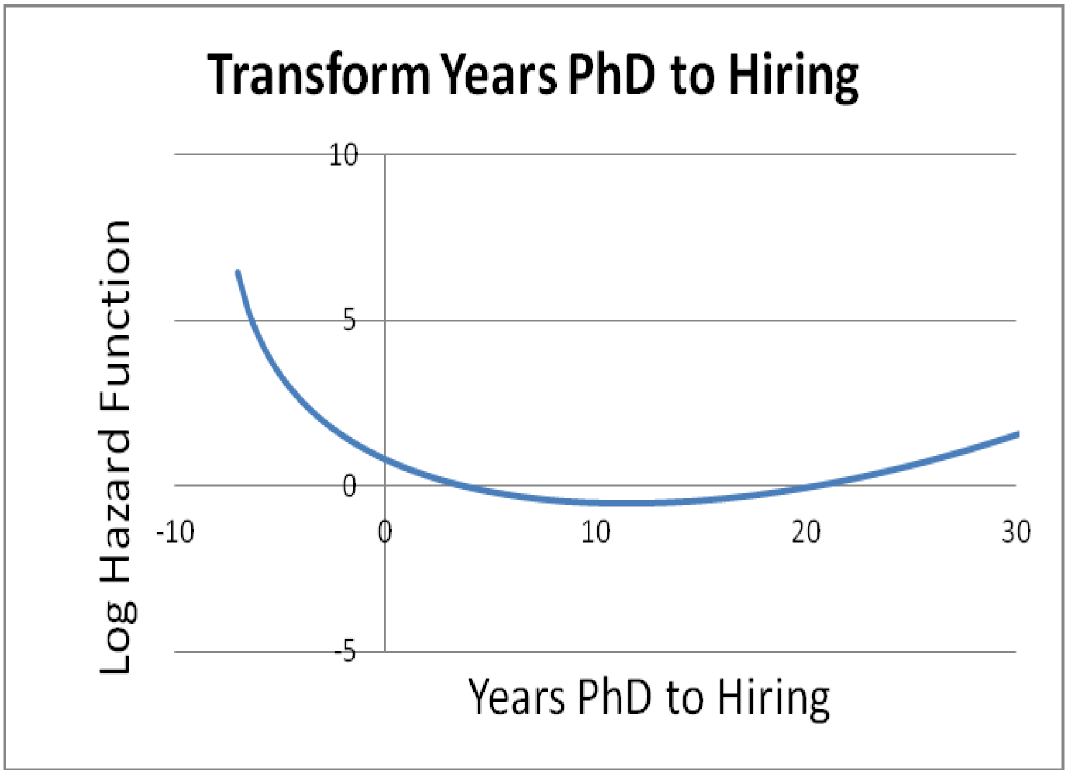

Figure 7. Bottom: Plot of log hazard function = -1.95{ln[(x+8)/10] – 0.19} + 0.24{[(x+8)/10]^2 – 1.45} vs. years from PhD to hiring.

The transform selected by Stata combines

PhDHire(1) = ln(X) – 0.18547 and

PhDHire(2) = X^2 – 1.44910,

where X = (PhDHire + 8)/10. The bottom of Figure 7 shows that the calculated transform using the regression coefficients matches the functional form shown in the top of Figure 7. This complex transform reflects the differing speed of promotion as reviewed above. The Stata program transforms the data and estimates the coefficients to generate a Cox regression model.

An example of the Cox regression model fit by the Stata fractional polynomial algorithm is shown in Table 21.

Table 21. Stata's Fractional Polynomial Algorithm Results for Professors.

Associate Professors

Cox regression		=-- Breslow method		for	ties	
Entry time _t0				Number of obs =		449
				LR chi2(9) =		122.24
				Prob > chi2 =		<0.00005
Log likelihood =		-2291.07		Pseudo R2 =		0.026

Variable	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
PhDHire(1)	-1.95096	0.291902	-6.68	<0.0005	-2.52308	-1.37884
PhDHire(2)	0.242054	0.06058	4.00	<0.0005	0.12332	0.360789
HirPubs	0.11994	0.025278	4.74	<0.0005	0.070396	0.169483
AscPPubs	-0.02135	0.006565	-3.25	0.001	-0.03422	-0.00849
NumMoves	-0.30582	0.119578	-2.56	0.011	-0.54019	-0.07145
Geog	0.229427	0.10911	2.10	0.035	0.015576	0.443279
Human	0.002179	0.001461	1.49	0.136	-0.00068	0.005042
CitAscP	0.000104	0.000135	0.77	0.439	-0.00016	0.000369
MovePhD	0.081638	0.139057	0.59	0.557	-0.19091	0.354185
Deviance:	4582.141.					

Table 21. Stata's Fractional Polynomial Algorithm Results for Professors (continued).

Full Professors

Cox Regression	Breslow method	for ties	
Entry time _t0		Number of obs =	261
		LR chi2(7) =	23.61
		Prob > chi2 =	0.0013
Log likelihood =	-1202.2	Pseudo R2 =	0.0097

Variable	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
PhDHire	-1.45862	0.46709	-3.12	0.002	-2.3741	-0.54314
HirePubs	0.103776	0.042632	2.43	0.015	0.020218	0.187334
PhD<89	-0.34376	0.151768	-2.27	0.024	-0.64122	-0.0463
White	-0.34983	0.172594	-2.03	0.043	-0.68811	-0.01156
HirsCite	-0.00063	0.000936	-0.67	0.501	-0.00246	0.001204
Gender	-0.0684	0.13713	-0.50	0.618	-0.33717	0.20037
CitAscP	-5.9E-05	0.000172	-0.34	0.733	-0.0004	0.000278
Deviance:	2404.328.					

*Deviance is two times the maximized log likelihood

Two strong predictors emerge for promotion of both associate and full professors: (1) years between PhD and hiring as an assistant professor (PhDHire) and (2) cumulative publications when hired (HirPubs, see Table 20). Otherwise the low-p-value predictors of promotion differ in associate and full professors.

Models varying from 8 to 15 variables were selected by increasing the univariate p-value cutoff for candidate variables to include in the Cox models for associate professors from $p < 0.01$ to $p < 0.15$ as shown in Table 22.

Table 22. Cox Regression Model for Associate Professor Variables and Their p-Values.

Associate Professors

		p-Value Cutoff		
		p<0.01	p<0.06	p<0.15
Variables	Candidates	9	12	16
	In Model	9	12	16
Sample Size (N)		449	418	370
Yrs PhD to Hire	**PhDHire**	<0.0005	<0.0005	<0.0005
Publications	**AscPubs**	0.001	0.002	0.003
	HirePubs	<0.0005	<0.0005	<0.0005
Citations	AscPCites	0.439	0.949	0.710
Focus	Geog	0.035	0.151	0.042
	Human	0.136	0.043	0.058
	Physical			0.631
	Other (%)			0.198
Gender	Gender	(0.007)	(0.032)	(0.014)
Moves	to PhD Granting	0.557	0.792	0.834
	Number	0.011	0.077	0.038
Grant Funding	Years		0.102	0.171
Voting	Demo		0.016	0.04
Hours Spent	Administration			0.027
PhD Cohort	1989-1997		0.217	0.761
	> 1997		0.778	0.116

Increasing the cutoff p-value led to larger Cox regression models as none of the candidate variables were excluded from the model. The sample size falls with larger models because the analysis only used professors with complete data and missing questionnaire responses lead to fewer professors with complete data. The smallest model, variables with a p-value cutoff of < 0.001, identifies the highly significant variables as well as the larger models. For example, the three relatively strong predictors, shown in bold, are identified in the smallest model with two strong predictors being identified by all models.

When gender is forced into the Cox regression models for associate professors its coefficient is significant (shown in parentheses in Table 22).

A similar analysis was done for full professors, as shown in Table 23, where the cutoff p-value used to select the Cox regression model was increased from p < 0.03 to p < 0.12.

Table 23. Cox Regression Model for Full Professor Variables and Their p-Values

Full Professors

		p-Value Cutoff		
		p<0.03	p<0.09	p<0.12
Variables	Candidates	7	9	12
	In Model	7	9	12
Sample Size (N)		261	241	186
Yrs PhD to Hire	PhDHire	**0.001**	**0.002**	**<0.0005**
Publications	HirePubs	**0.006**	**0.023**	**0.109**
Citations	HireCites	0.437	0.623	0.875
	AscPCites	0.67	0.867	0.702
	ProfCites			0.977
Cohort	< 1989	0.011	0.029	0.039
Race	White	**0.012**	**0.007**	**0.046**
Focus	Geog		0.288	0.228
	Other (%)		0.919	0.403
Gender	Gender	0.555	0.607	0.650
Grant Funding	Amount			0.450
Spouse Works	Full-time			0.059

The coefficient p-values are more variable for full professors, probably reflecting their smaller sample size. As with the associate professors models, all candidate variables are included in the Cox regression model, the sample size falls with increasing model size, and the smallest model identifies stronger predictors as well as the larger models. Gender is not significant in any of the models, but years between granting of their PhD and hiring as an assistant professor (PhDHire), cumulative publications when hired (HirePubs) and white race were significant and shown in bold in Table 22.

Smaller models appear to identify strong predictor variables, but it is important to see if the values of the coefficients are about the same in models of different size (see Table 24).

Table 24. Variability of Coefficients in Cox Regression Models for Associate Professors.

p-Value Cutoff

		0.01	0.06	0.15	% Difference
Experience	**PhdHire**	-1.951	2.24105	-2.1343	8.6*
		0.24205		0.28768	15.9
Publications	**AscPubs**	-0.0214	-0.0188	-0.0206	12.1
	HirePubs	0.11994	1.5726	0.12072	0.6
Citations	AscPCites	0.0001	-9.25E.06	5.3E-05	108.9
Focus	Geog	0.22943	0.17142	0.26487	35.3
	Human	0.00218	0.00342	0.00437	50.1
	Physical			0.00098	
	Other (%)			0.00263	
Gender		(-0.27206)	(-0.25087)	(-0.2758)	9.0
Moves	PhD Granting	0.08164	-0.0408	-0.0323	26.1
	Number	-0.3058	-0.2371	-0.2861	6.9
Grant	Years			0.01229	
Voting	Democratic		-0.2989	-0.2656	12.6
Hours	Administration			0.01076	
Cohort	89-97		-0.15993	-0.05052	68.4
	> 1997		0.038372	0.291738	86.8

* Compared 0.01 and 0.15 coefficients where both transforms were log; a square root transform was used for 0.06 coefficient.

Often the coefficients varied by less than 20%, but a few large differences were observed. The large variation in the AscPCites, or the cumulative associate professor citations, variable may be explained by the p-values of its coefficient being more than 0.7 in all models. Gender was forced into the associate professors and varied little once included in the regression model. One problem is that Stata calculates slightly different transforms for the same variable as it adjusts the transform for the presence of other variables. Occasionally, Stata used different transforms. An example is PhDHire, or number of years between awarding of a professor's PhD and starting work as an assistant professor, where the Stata algorithm selected a log transform in the compared coefficients and a square root transform with the other coefficient. Generally the coefficients of the strong predictors, shown in bold, vary by less than about 12%.

The coefficients of the full professor's variables were more variable as shown in Table 25.

Table 25. Variability of Coefficients in Cox Regression Models for Full Professors.

		p-Value Cutoff			
Category	Variable	0.05	0.1	0.25	% Difference
Experience	PhDHire	-0.01475	-0.6077	-1.02462	
		0.5052022	0.53768	0.106697	
Publications	**HirePubs**	0.117809	0.11476	0.077589	2.6
Citations	HireCites	-0.00105	-0.0008	-0.00042	18.9
	AscPCites	-1.20E-05	1.22E-05	1.67E-05	38.6
	ProfCites			-1.80E-05	
Race	**White**	-0.41197	-0.4663	-0.40152	13.9
Focus	Geog		0.19022	1.99E-01	
	Other	-0.0015	-0.0008	-0.00268	
Gender		-0.04959	-0.1293	8.03E-03	106.2
Cohort	< 1989	-0.4280453	-0.41914	-0.3910935	8.6
Grant	Amount		1.19E-08	-1.17E-09	
Spouse Works	Full-time			-0.32392	

The full professor coefficients are more difficult to compare as their transforms were more variable. The two relatively strong predictors, shown in bold, have a relatively small percent variation when similarly transformed coefficients are compared; gender is quite variable which may reflect its relatively large p-values of its coefficient, ranging from 0.555 to 0.650.

In this study professors were matched by gender, on the year their PhD was granted, and being assistant professors in the same PhD-granting institution. This matching could be considered to stratify two groups that could be analyzed by a stratified Cox regression model (Hosmer, Lemeshow and May 2008, 208-213). Stratified Cox regression generates one set of coefficients for the variables included in the model, but a separate analysis can then be done for the stratifying variables such as gender; this gives gender specific coefficients for each variable (Hosmer, Lemeshow and May 2008, 208-213). Since gender is a binary variable, comparing the male and female model coefficients is the same as checking for an interaction of gender with each of the variables included in the model; gender interactions are the most commonly noted in the literature (Astin and Bayer 1972, 111, 112-113; Bayer and Astin 1975, 799-800; Ginther and Hayes 2003, 55; Ginther and Kahn 2004, 202-205; Ginther and Kahn 2006, 8; Long, Allison, and McGinnis 1993, 711, 716). Stratifying by institution was more complex as there were 74 institutions and no commonly accepted ranking system for all the institutions. In the literature top ranked programs have been distinguished (Ginther and Hayes 2003, 39; Ginther and Kahn 2004, 200; Ginther and Kahn 2006, 24; Long, Allison, and McGinnis 1993, 710) and the National Research Council's 1995 rankings were used to dichotomize assistant professors who were hired by top-ranked institutions (TopAssP) and other programs (see METHODS for listing). Similarly, the year of PhD-granting was divided into those awarded before 1989 (PhD<89), between 1989 and 1997 (PhD8997), and after 1997 (PhD>97) in an attempt to create three groups approximately equal in size. This simplification permits the calculation of coefficients separately for assistant professors working at top ranked programs vs. other programs and for three cohorts of PhDs.

One situation where a stratified Cox regression model is needed is when a variable has hazard or survival curves which cross; this means that the proportional hazard assumption is not met for that variable (Kleinbaum and Klein 2005, 14, 107-111, 137-145). Kaplan-Meier survival curves were estimated for each of the binary variables in the Cox regression models for associate and full professors. The survival curves did not cross for gender, but did cross for professors hired at a top-ranked institution and for the PhD cohorts for full professors, as shown in Figure 8.

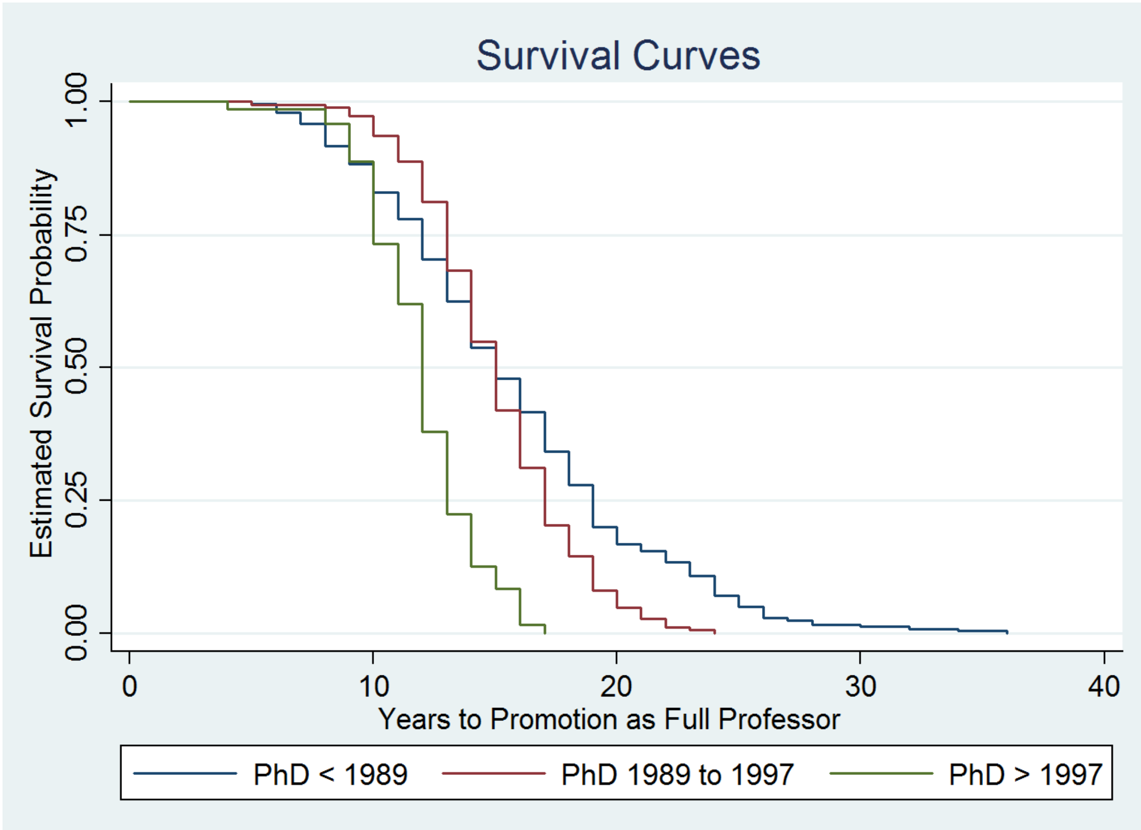

Figure 8. Plot of estimated survival probability vs. years to promotion as a full professor for three PhD cohorts. Professors with PhD granted before 1989 are shown in blue, professors with their PhDs granted between 1989 and 1997 are shown in red, and professors with their PhDs granted after 1997 are shown in green. Note that the survival curves cross.

The three cohorts of professors who received their PhDs before 1989, between 1989 and 1997, and after 1997 had significantly different survival curves (full professors, log rank test, χ^2 = 80.94, df = 1, p = <0.00005). Similar and equally significant results were found with associate professors. The cohort awarded their PhDs before 1989 seems the most variable; initially they were a little faster to be promoted to become associate professors and full professors and then over the years slower to be promoted to become associate and full professors. The most recent cohort, granted PhDs after 1997, are initially a bit slower to be promoted to become associate professors and then faster to become both associate and full professors. The cohort receiving their PhDs between

1989 and 1997 are a little slower to become associate professors and full professors, but later are intermediate in their rate of becoming full professors. The results for the cohort receiving their PhDs after 1997 may be biased in their survival curves for full professors as many may not have enough time to become full professors and their seemingly rapid promotion may reflect the lack of time for the remaining associate professors of that cohort to be promoted. Crossing of the survival curves for professors hired at top-ranked institutions vs. not was slight and limited to the early years of the survival curves. The Cox regression models for associate and full professors did not need to be stratified as they did not include variables with survival curves which cross.

Even if a stratified Cox regression model was not used, it would be interesting to know how variable Cox regression models are when used on the current data set. The results of a stratified Cox regression model for associate and full professors are shown in Table 26 in the APPENDIX. The Cox regression was stratified by gender, institution, and year of PhD-granting. The coefficients in the stratified and non-stratified Cox regression models were similar in the associate professor models, but more variable in the full professor models (see Table 27).

Table 27. Comparison of Coefficients for Stratified and Non-Stratified Models.

Associate Professor

Variable	Stratified Coefficient	P>z	Not Stratified Coefficient	P>z	Coefficient % Change
PhDHire (1)	-2.03136	<0.0005	-1.95096	<0.0005	4.0
PhDHire (2)	0.249248	<0.0005	0.242054	<0.0005	2.9
HirPubs	0.127905	<0.0005	0.11994	<0.0005	6.2
AscPPubs	-0.02423	0.001	-0.02135	0.001	11.9
NumMoves	-0.36395	0.004	-0.30582	0.011	16.0
Geog	0.302344	0.008	0.229427	0.035	24.1
Human	0.001748	0.25	0.002179	0.136	19.8
CitAscP	0.000109	0.435	0.000104	0.439	4.1
MovePhD	0.080749	0.588	0.081638	0.557	1.1

Professors

Variable	Stratified Coefficient	P>z	Not Stratified Coefficient	P>z	Coefficient % Change
PhDHire (1)	-1.89969	<0.0005	-1.45862	0.002	23.2
PhD <89			-0.34376	0.024	
White	-0.3883	0.06	-0.34983	0.043	9.9
HirePubs	0.147878	0.005	0.103776	0.015	29.8
Gender			-0.0684	0.618	
CiteAscP	-0.0002	0.371	-5.9E-05	0.733	70.4
HireCites	-0.00099	0.398	-0.00063	0.501	36.2

As before the variability of stronger predictors is usually less than that of the weaker predictors, but differences in the transforms used by the multiple fractional polynomial algorithm limit this analysis. The coefficients for the Cox regression models with and without stratification for both associate and full professors were compared and no significant differences were detected. This analysis shows that the model's coefficients are relatively similar even when estimated in different ways.

Gender specific coefficients were calculated for male and female associate professors using Cox regression as shown in Table 28 in the APPENDIX. The gender specific coefficients for PhDHire (time between PhD-granting and hiring as an assistant professor), HirePubs, and AscPPubs (publications before hiring and promotion to become an associate professor) were usually significant within the Cox regression model, although the relationship was less significant for females. Some variables differed with a geography research focus (Geog) and number of moves as an assistant professor (NumMoves) being statistically significant for males but not females. Part of the difference in the significance for females is their sample size is smaller.

The gender specific coefficients from the stratified Cox regression model for full professors are shown in Table 29 in the APPENDIX. The male Cox regression model is statistically significant, but the female model is not significant. The significant coefficients for males are HirePubs (cumulative publications when hired) and white race. A larger sample of female professors may have made the HireCites coefficient reach statistical significance.

A comparison of the gender specific coefficients from the Cox regression model for associate and full professors is shown in Table 30.

Table 30. Comparison of Male and Female Coefficients for Associate and Full Professors.

Associate Professors (Not Stratified)

	Coefficients				Comparisons of	
	Male		Female		Coefficients	
Variables	Mean	Std. Err	Mean	Std. Err	t-test	p-value
PhDHire (1)	-19.6858	4.159852	-26.1513	5.22687	0.967866	0.33428
PhDHire (2)	7.693704	1.757611	9.699584	2.143111	0.72371	0.47009
HirPubs	0.202069	0.038125	0.141079	0.079616	0.690925	0.490414
AscPPubs	-0.04433	0.010319	-0.04912	0.018089	0.230022	0.81831
CitAscP	0.00014	0.000175	0.000739	0.000485	1.162086	0.246585
Geog	0.452502	0.167395	0.146659	0.215404	1.121123	0.26358
Human	0.003389	0.002251	0.00566	0.002844	0.626238	0.531873
MovePhD	0.10724	0.22201	0.20161	0.3245	0.240019	0.810561
NumMoves	1.115985	0.282629	0.502959	0.429964	1.191414	0.234903

Professors (Stratified Cox Regression)

	Coefficients				Comparisons of	
	Male		Female		Coefficients	
Variables	Mean	Std. Err	Mean	Std. Err	t-test	p-value
HirePubs	0.201653	0.050884	-0.00926	0.124016	1.57341	0.11654
White	-0.62823	0.226468	-0.39113	0.325329	-0.59814	0.55014
FocusOth	-0.00365	0.002432	-0.00012	0.003066	-0.90220	0.36758
HireCites	-0.00141	0.001102	0.008045	0.004940	-1.86787	0.06263
CitAscP	-5.7E-05	0.000207	1.17E-06	0.000526	-0.10352	0.91761
PhDHire	-0.00219	0.016959	-0.03135	0.022684	1.02958	0.30393

The gender specific coefficients were more variable in relatively weak predictors and in full professors, where the sample size was smaller. The gender specific coefficients were compared using Cox regression, both stratified and not stratified, for associate professors and full professors: no significant difference was detected.

In Cox regression models for associate professors, gender had a significant and negative coefficient. How much does gender slow promotion? This was evaluated by displaying Kaplan-Meier survival curves (Hosmer, Lemeshow, and May 2008, 17-26; see Figures 9 and 10).

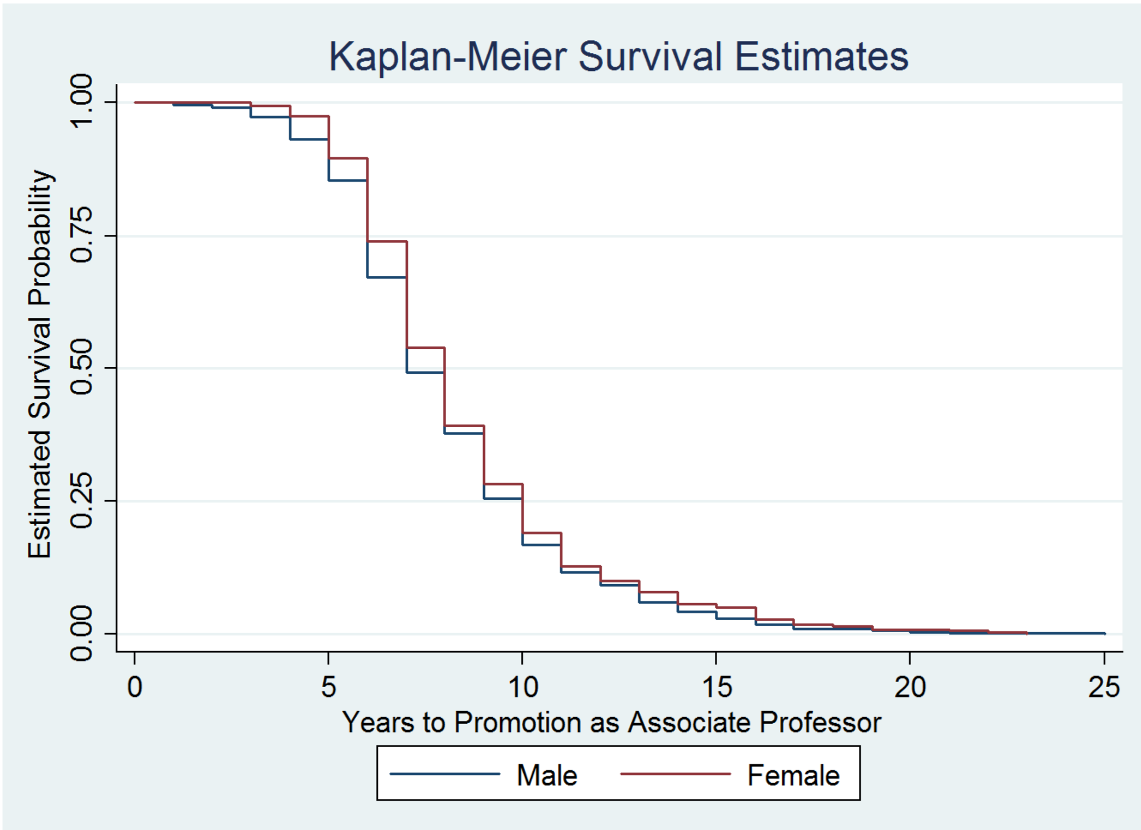

Figure 9. Plot of estimated survival probability vs. years to promotion as an associate professor. Males are shown in blue and females in red.

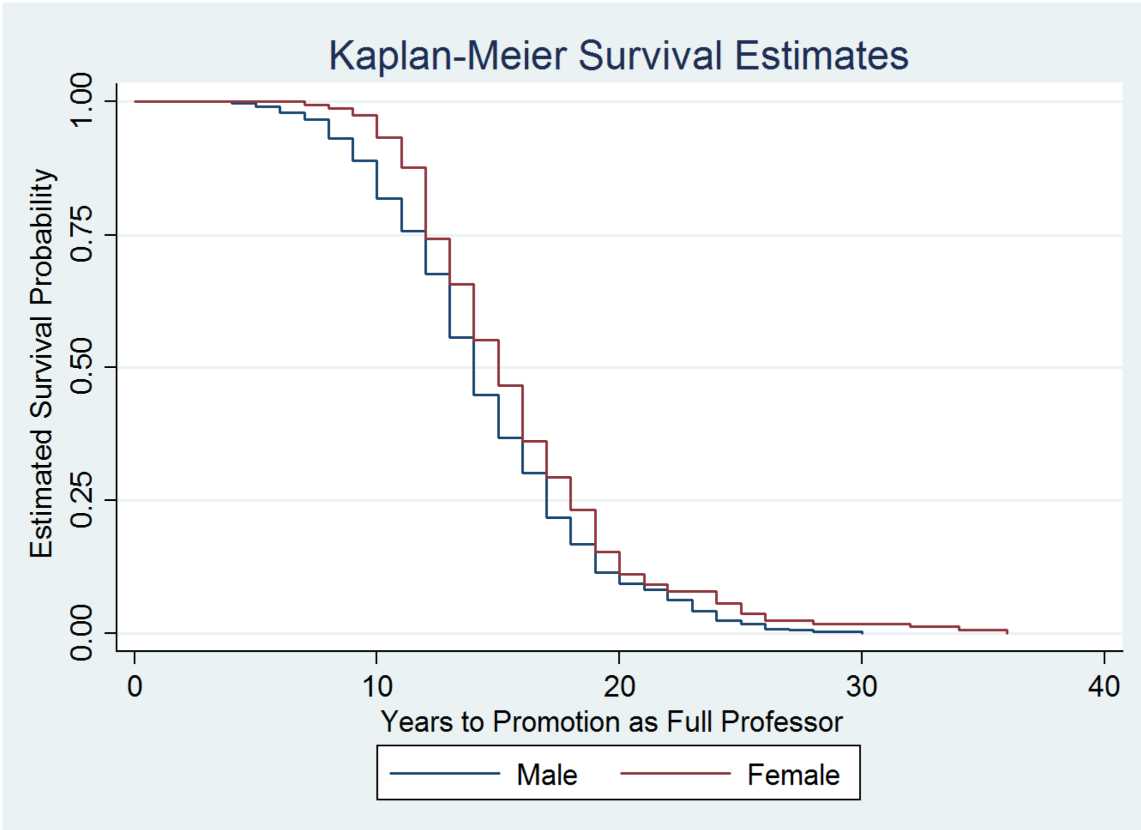

Figure 10. Plot of estimated survival probability vs. years to promotion as a full professor. Males are shown in blue and females in red.

Males are promoted more rapidly than females to the ranks of associate and full professor; these differences were not significant for associate professors (log rank test: χ^2 = 2.37, df = 1, p = 0.1238) but were significant for full professors (log rank test: χ^2 = 6.46, df = 1, p = 0.0110). The answer to the second research question is that the proportion of females promoted at each time is less than that of men, although this difference if only statistically significant for full professors. If the proportional hazard assumption is met then the survival curves for gender should not cross, which is true (Kleinbaum and Klein 2005, 107-111, 137-145).

The three PhD cohorts; with PhDs granted before 1989, between 1989 and 1997, and after 1997; had different rates of promotion (see Figure 8 above) and would be expected to differ in one of the most significant predictors of promotion, cumulative publications when hired (HirePubs, see Table 31).

Table 31. Publications When Hired in PhD Cohorts.

Cumulative Publications when Hired

PhD Cohort	Mean	Std Dev	N
<1989	1.14	1.95	280
1989-1997	1.73	2.61	282
>1997	2.06	2.52	307

ANOVA: Model $F = 13.71$, $df = 2$ and 863, $p < 0.00005$.
for <1989 cohort $F = 27.64$, $df = 1$, $p < 0.00005$; for PhD between 1989 and 1997 $F = 24.49$, $df = 1$, $p < 0.0253$.

The distribution of HirePubs is skewed so the calculation was repeated using the Wilcoxon rank sum test, which confirmed these difference. This suggests that differences in speed of promotion, slowest for those with granted before 1989 and fastest for those with PhDs granted after 1997, may be related to publications when hired. Likewise, speed of promotion in the three PhD cohorts might also relate to differences related to PhDHire, or the years between awarding of a PhD and hiring as an assistant professor.

The relationship between PhDHire in the three PhD cohorts is shown in Table 32.

Table 32. Distribution of Years from PhD to Hiring in Three PhD Cohorts.

PhD Cohort	Years PhD Granting to Hire			Total
	< 0	0 to 15	> 15	
<1989	11	238	31	280
1989-1997	12	265	5	282
>1997	12	295	0	307
Total	35	798	36	869

Table 32 shows the number of professors in each category. One obvious difference is the drop in professors hired more than 15 year after their PhD was granted; the overall χ^2 test of the table was significant (χ^2 = 51.2, df = n – 1 = 4, p < 0.0005). When the three PhD cohorts were examined individually only the cohort with PhDs granted after 1997 was significantly different from the earlier PhD cohorts (χ^2 = 49.0, df = n – 1 = 2, p < 0.0005). Professors hired before their PhDs were granted were approximately equally represented in all three PhD cohorts.

The estimated coefficients in the Cox regression models, $\hat{\beta}$, are related to the estimated hazard ratio ($\widehat{\mathrm{HR}}$) with $\widehat{HR} = e^{\hat{\beta}}$ where x is binary (Kleinbaum and Klein 2005, 100-103). For many variables the estimated hazard ratio, $\widehat{\mathrm{HR}}$, is the ratio of two estimated hazard functions or

$$\widehat{\mathrm{HR}} = \frac{\hat{\mathrm{h}}(\mathrm{t},\mathrm{X}^*)}{\hat{\mathrm{h}}(\mathrm{t},\mathrm{X})} = \frac{\hat{\mathrm{h}}_0(\mathrm{t})e^{\sum_{i=1}^{k}\beta_i X_i^*}}{\hat{\mathrm{h}}_0(\mathrm{t})e^{\sum_{i=1}^{k}\beta_i X_i}} = \exp\left[\sum_{i=1}^{k}\beta_i(X_i^* - X_i)\right], \qquad (13)$$

where X_i^* are the k-independent variables for one group and X_i are the k-independent variables for the other group (Klein and Moeschberger 2003, 243-245; Kleinbaum and Klein 2005, 100-101). The calculation of the estimated hazard ratio assumes that the ratio of the estimated baseline hazard functions is constant ($\hat{\theta}$), or

$$\frac{\hat{\mathrm{h}}(\mathrm{t},\mathrm{X}^*)}{\hat{\mathrm{h}}(\mathrm{t},\mathrm{X})} = \hat{\theta}, \qquad (14)$$

which implies that the two hazard curves should not cross (Kleinbaum and Klein 2005, 107-111). Further, the estimated hazard ratio should not depend on time (Kleinbaum and Klein 2005, 134-135).

An estimated survival curve, S(t), varies between 0 and 1, but can be transformed with –ln[-ln(S(t))] into a variable which extends from ±∞ (Kleinbaum and Klein 2005, 137-141). A useful trait of the -ln[-ln(S(t))] transform is that it should have no trend over time (Kleinbaum and Klein 2005, 137-141). As a result if the proportional hazards assumption is true then plots of -ln[-ln(S(t))] will be linear and violations of the assumption can be visually assessed as shown in Figure 11 for associate professors and Figure 12 for full professors.

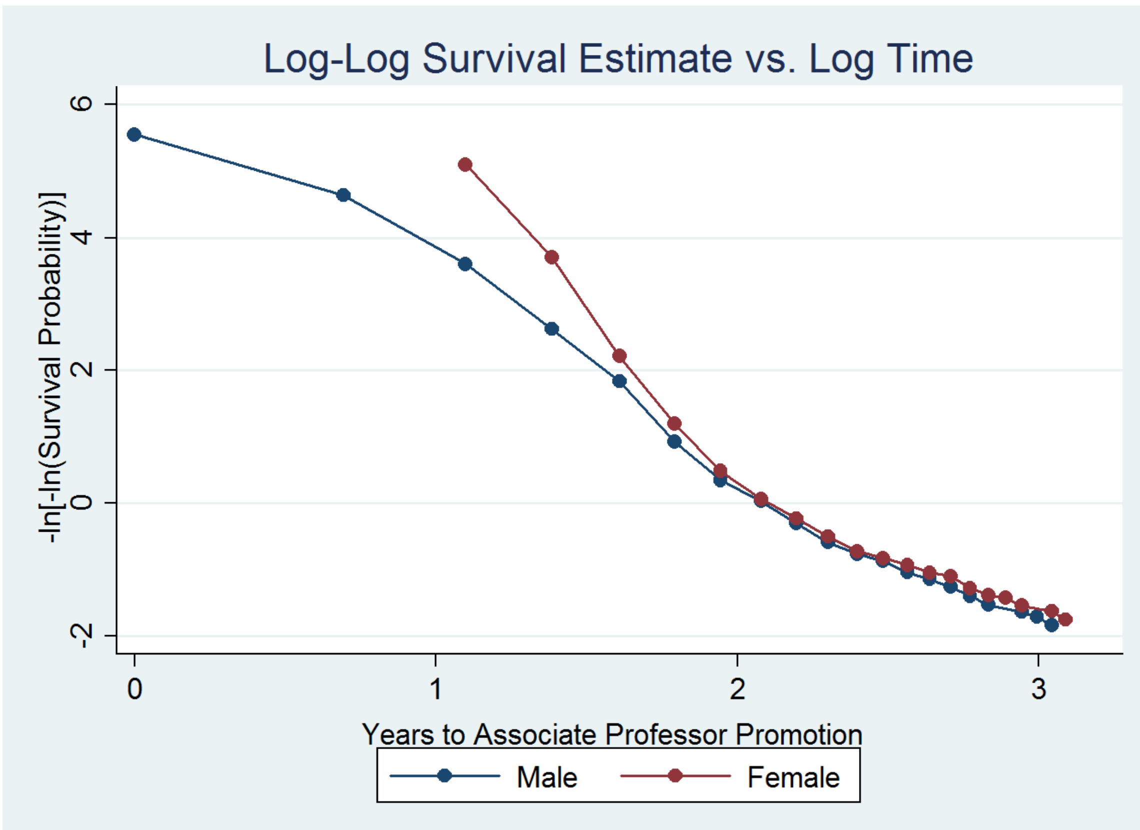

Figure 11. Plot of the –ln(-ln) transform of the survival probability vs. the natural log of years to promotion as an associate professor. Males are shown in blue and females in red. Scale is ln(years) where ln(2.7 years) = 1 and ln(7.4 years) = 2.

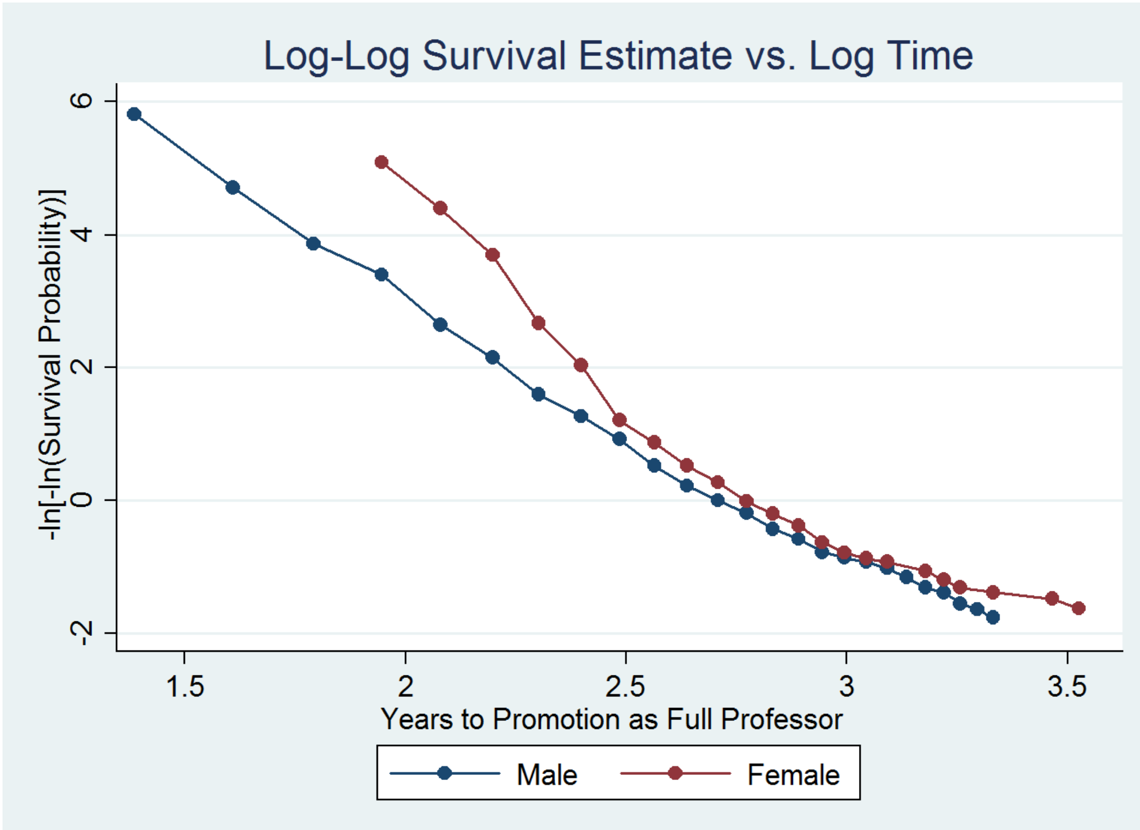

Figure 12. Plot of the –ln(-ln) transform of the survival probability vs. the natural log of years to promotion as a full professor. Males are shown in blue and females in red. Scale is ln(years) where ln(11 years) = 2.4 and ln(26 years) = 3.26.

As Figure 11 shows the transformed years to promotion as an associate professor are approximately the same for males and females after 2 on the log scale which is about 7.4 years. Similarly, male and female full professors are similar after about 11 years, with ln(11 years) = 2.4. The Cox regression model, shown in Figure 12, was similar to an equivalent Cox regression model which was stratified. Males become associate and full professors more rapidly than females, although few become associate professors in less than ln(2.7 years) = 1 or full professors in less than ln(11 years) = 2.4. Small sample size may explain the divergence of the –ln(-ln) curves as log time falls from 2 or 2.4 to 1. The male and female ln-ln(survival estimates) converge after ln(time) = 2 for associate professors and after ln(time) = 2.4 for full professors and are approximately linear.

Hosmer, Lemeshow and May (2008, 177-184) have suggested a way to test if individual variables meet the proportional hazards assumption. Unfortunately, Cox regression does not provide estimated value for each observed value and as a result the usual residuals of estimated minus observed are lacking (Hosmer, Lemeshow and May 2008, 170). This void has been filled by other residuals, such as Schoenfeld's partial residuals (Hosmer, Lemeshow and May 2008, 170-177). Plots of scaled Schoenfeld residuals over time for a given variable should on average be approximately zero (Hosmer, Lemeshow and May 2008, 177-184; see Figure 13).

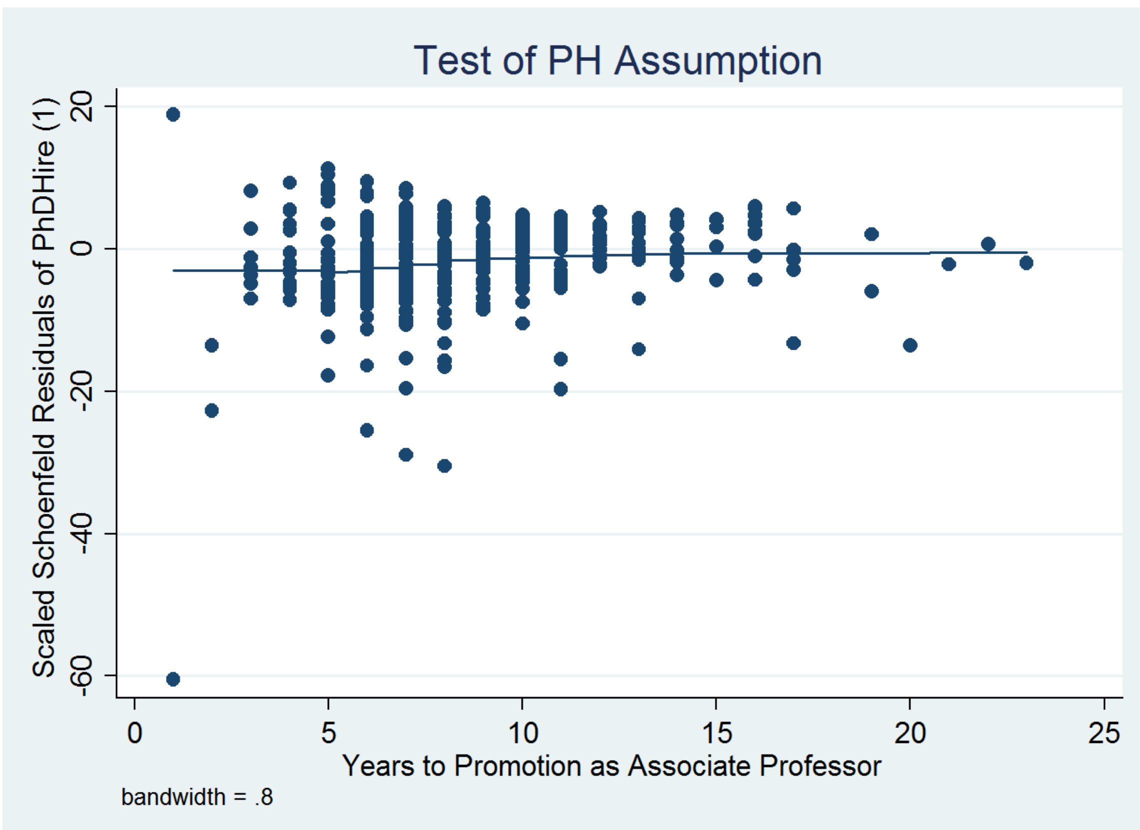

Figure 13. Plot of scaled Schoenfield residuals of PhDHire (1) vs. years to promotion as an associate professor. Line is smoothed residuals and dots are individual residuals. PhDHire is the years between granting of PhD and when hired as an assistant professor.

The plot of the smoothed, scaled Schoenfeld residuals of the PhDHire(1) (years between granting of PhD and hiring as an assistant professor) vs. years to promotion as an associate professor is approximately zero over time; the significance of these deviations is evaluated visually (Hosmer, Lemeshow and May 2008, 177-184). Similar results were found with the all the other variables, including the cohort of PhDs granted before 1989;

Graphical techniques are available to identify highly influential observations, sometimes called outliers (Klein and Moeschberger 2003, 385). Schoenfeld's partial residuals, or efficient score residuals in Stata, can be used to identify individual observations which produce large changes in the estimate of a given coefficient (Hosmer, Lemeshow and May 2008, 184-191; Klein and Moeschberger 2003, 385; see Figure 14).

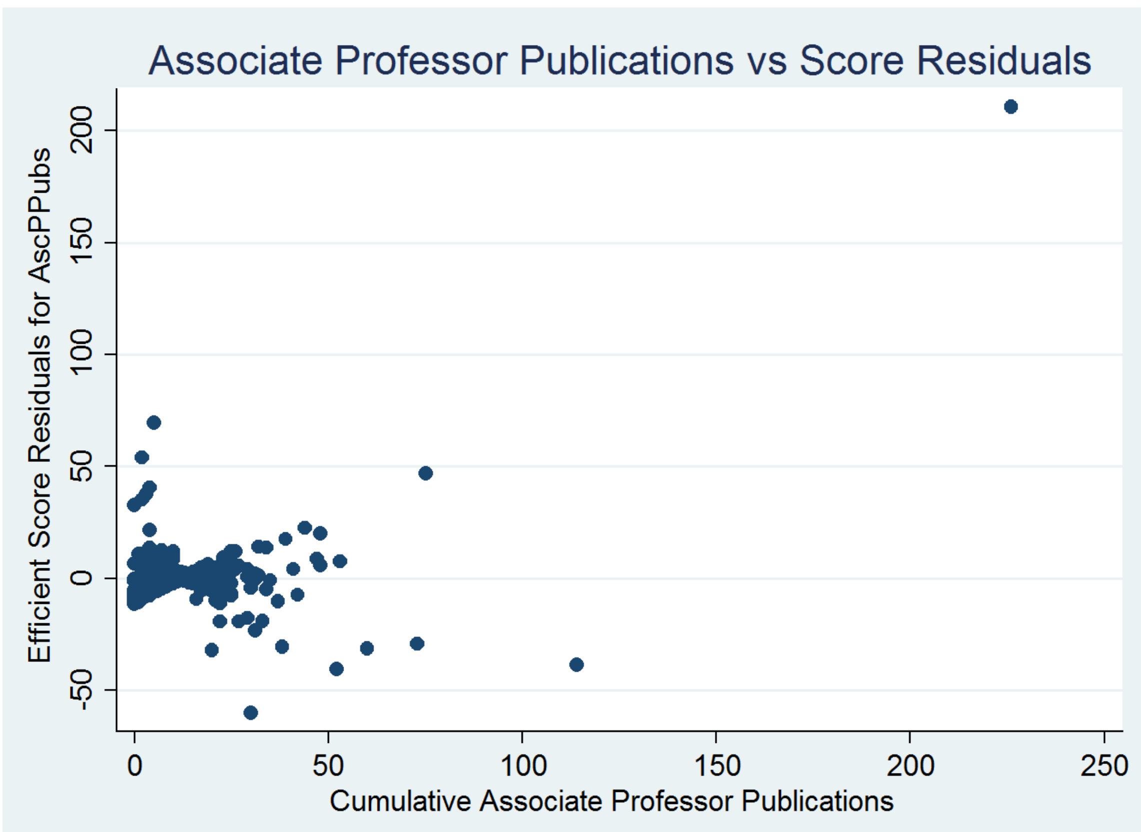

Figure 14. Plot of efficient score residuals vs. cumulative associate professor publications (AscPPubs). The residuals, shown as dots, seem to cluster approximately about zero, but there is one unusual value.

As Figure 14 shows most of the efficient score residuals cluster within about ±50 of the x-axis, but one value is highly influential. Four highly influential values were identified in two associate professors and one full professor; data from these three professors was correctly coded in the database and these three professors were deleted.

The overall fit of the Cox regression model can be evaluated using Cox-Snell residuals (Box-Steffensmeier and Jones 2011, 120; Cleves et al. 2010, 219-223; Klein and Moeschberger 2003, 354-359; see Figures 15 and 16).

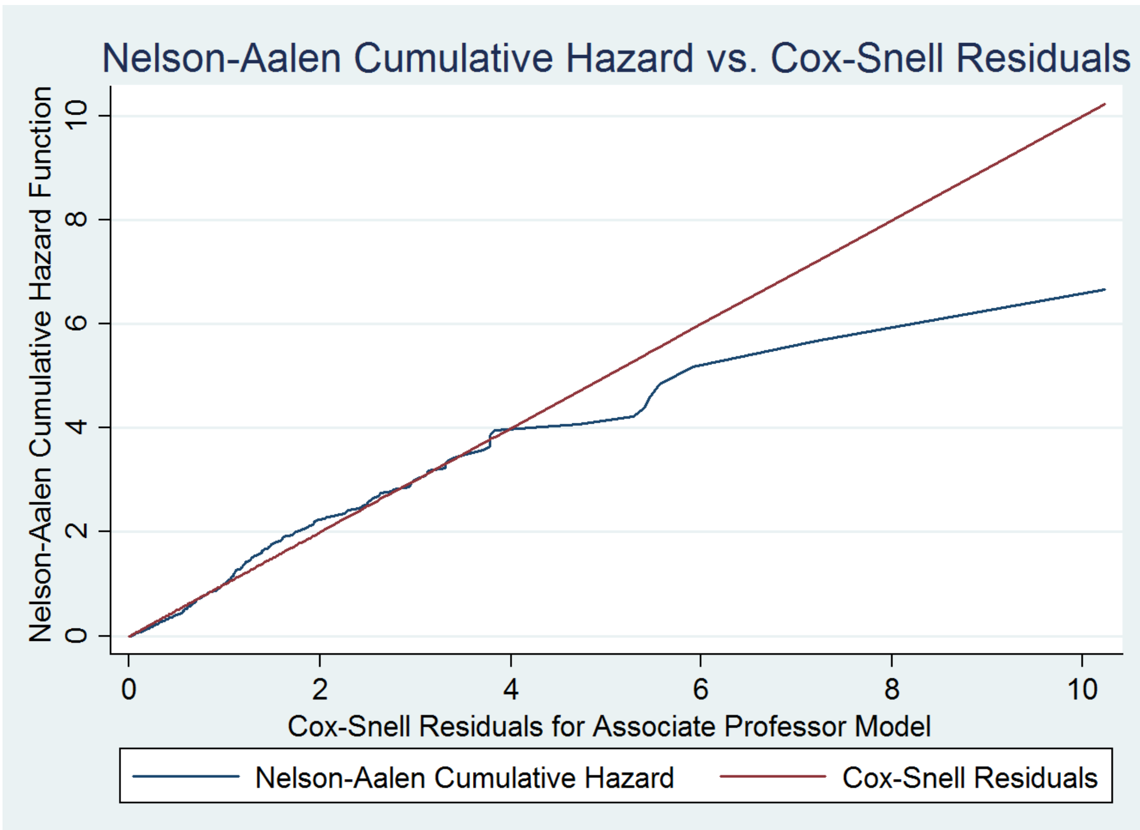

Figure 15. Plot of Nelson-Aalen cumulative baseline hazard vs. Cox-Snell residuals for associate professors. Residuals are shown in blue and red line has a slope of one and y-intercept of zero.

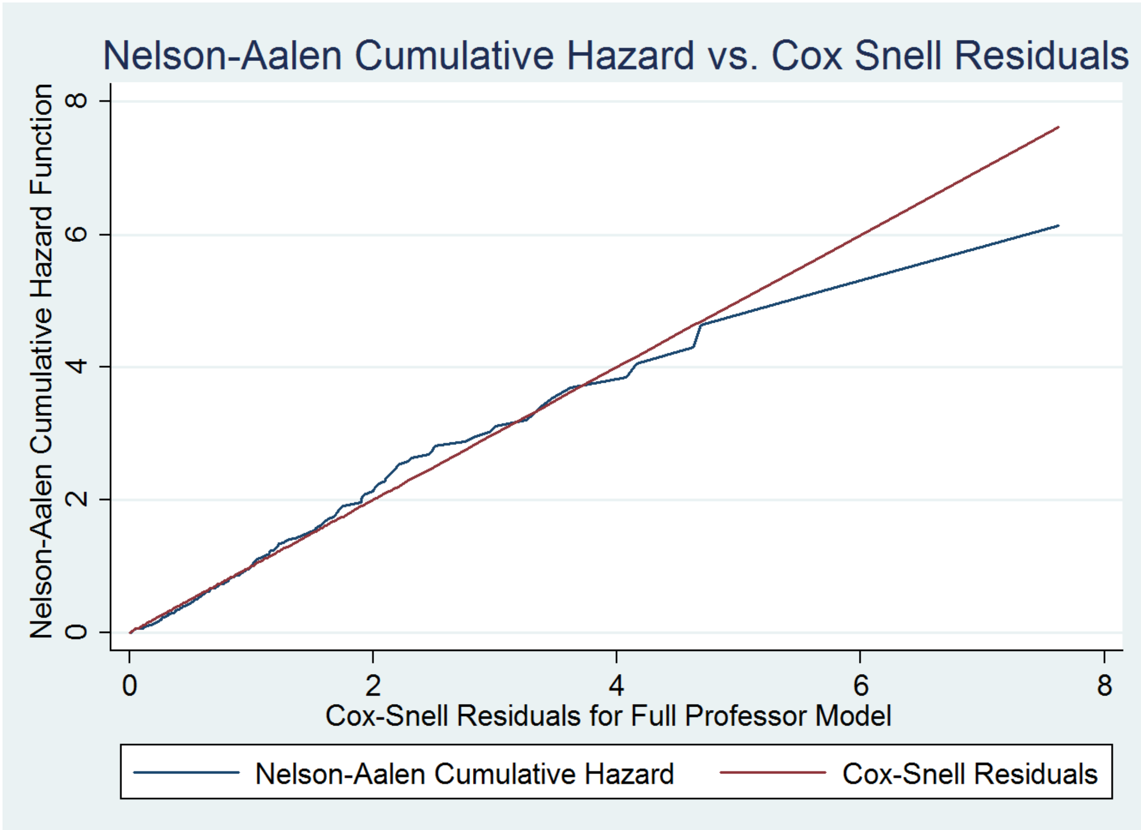

Figure 16. Plot of Nelson Aalen cumulative baseline hazard vs. Cox-Snell residuals for full professors. Residuals are shown in blue and red line has a slope of one and y-intercept of zero.

A plot of the Cox-Snell residual along the abscissa vs. the Nelson-Aalen cumulative baseline hazard along the ordinate is expected to be a straight line with a slope of one and a zero intercept if the overall Cox regression model is valid (Box-Steffensmeier and Jones 2011, 120; Klein and Moeschberger 2003, 354-359; Tableman and Kim. 2004, 168-169). For both associate and full professors the overall model comes close to having a y-intercept of zero, but the slope of one with some divergence at the right tail as expected to censoring and reduced sample size (Cleves et al. 2010, 219-223). There is no statistical test to evaluate the significance of these deviations from the expected intercept of zero or slope of one (Box-Steffensmeier and Jones 2011, 120).

Table 33 shows the final Cox regression models.

Table 33. Final Cox Regression Models for Associate Professors.

Cox regression --		exact partial		likelihood for ties		
No. of subjects =		446		Number of obs =		446
No. of failures =		446				
Time at risk =		3703				
				LR chi2(10) =		202.4
Log likelihood =		-955.754		Prob > chi2 =		<0.00005

Variable	Haz. Ratio	Std. Err.	z	P>z	[95% Conf.	Interval]
PhDHire (1)	2.92E-10	9.31E-10	-6.89	<0.0005	5.69E-13	1.50E-07
PhDHire (2)	4125.497	5475.713	6.27	<0.0005	305.977	55624.21
HirePubs	1.185348	0.039095	5.16	<0.0005	1.111148	1.264503
AscPPubs	0.961502	0.007881	-4.79	<0.0005	0.946179	0.977073
NumMoves	2.658119	0.613053	4.24	<0.0005	1.691446	4.17725
Geog	1.459428	0.189057	2.92	0.004	1.132182	1.88126
Gender	0.74528	0.08937	-2.45	0.014	0.58918	0.942737
Human	1.003816	0.001748	2.19	0.029	1.000397	1.007247
MovePhD	1.324384	0.229502	1.62	0.105	0.942995	1.860024
AscPCites	1.000207	0.000163	1.27	0.203	0.999888	1.000527

Overall more variables are significant or more highly significant. Switching to the exact partial likelihood method for ties improves the fit of the model slightly. The estimated hazard ratio $\widehat{HR}$ is

$$\widehat{HR} = e^{\hat{\beta}}, \qquad (12)$$

where $\hat{\beta}$ is the estimated coefficient for the variable (Kleinbaum and Klein 2005, 100-103). The advantage of hazard ratios is that their interpretation is similar to that of an odds ratio (Kleinbaum and Klein 2005, 32). Thus, a hazard ratio of about 1.2 for HirePubs (cumulative publications when hired as an assistant professor) means one more publication when hired increases the hazard of promotion by 1.2 compared to no change in the number of publications; this is a 20% increase in the hazard of promotion, where the hazard is the instantaneous rate of change of the conditional probability of promotion, conditioned on survival to promotion (Kleinbaum and Klein 2005, 11, 32). Often this will be abbreviated and stated as an increase or decrease in the rate of promotion. The coefficients for both Cox regression models, stratified and not stratified, were about the same; there was no statistically significant difference between the coefficients in the two models using a t-test. Gender specific coefficients were compared and no significant differences were detected using a t-test. Gender reduces the hazard ratio to about 0.75, showing that the rate of promotion for females is about 25% slower than that of males (Kleinbaum and Klein 2005, 11, 32).

The final Cox regression models for full professors are shown in Table 34.

Table 34. Final Cox Regression Models for Full Professors.

Cox regression --	exact partial likelihood for ties		
No. of subjects =	261	Number of obs. =	261
No. of failures =	260		
Time at risk =	4005		
		LR chi2(8) =	42.76
Log likelihood =	-666.555	Prob > chi2 =	< 0.00005

Variable	Hazard Ratio	Std. Err.	z	P>z	[95% Con.	Interval]
PhDHire(1)	0.164704	0.087141	-3.41	0.001	0.058392	0.464572
PhDHire(2)	1.657321	0.247484	3.38	0.001	1.236797	2.220827
PhD<89	0.651782	0.109095	-2.56	0.011	0.469493	0.904848
White	0.654844	0.125506	-2.21	0.027	0.449778	0.953405
HirePubs	1.142114	0.054905	2.76	0.006	1.039415	1.254959
Gender	0.914364	0.138783	-0.59	0.555	0.679083	1.231161
AscPCites	0.999918	0.000193	-0.43	0.670	0.999541	1.000295
HirCites	0.999190	0.001041	-0.78	0.437	0.997152	1.001232

Like the associate professor Cox regression model, the hazard ratios for PhDHire (years between granting of their PhD and hiring as an assistant professor) and HirePubs (cumulative publications when hired) are highly significant with HirePubs increasing the rate of promotion about 14% which is a little less than the 19% increase seen with associate professors. Whites are about 35% slower to be promoted than other racial groups, which are dominated by Asians (see Table 16 in the APPENDIX***).*** The coefficients were compared for Cox regression models with and without stratification and were similar; there was no statistically significant difference between the coefficients of the models. Gender has no significant effect on promotion to full professor and gender specific coefficients were not statistically significantly different. Thus, the answer to the third research question in that when corrected for other variables, such as publications, the rate of promotion of females is slower than that of males to become associate professors, but not to become full professors.

Cox regression models can be adjusted for the mean of their covariates and then compared with Kaplan-Meier survival curves as shown in Figure 17 for associate professors and Figure 18 for full professors.

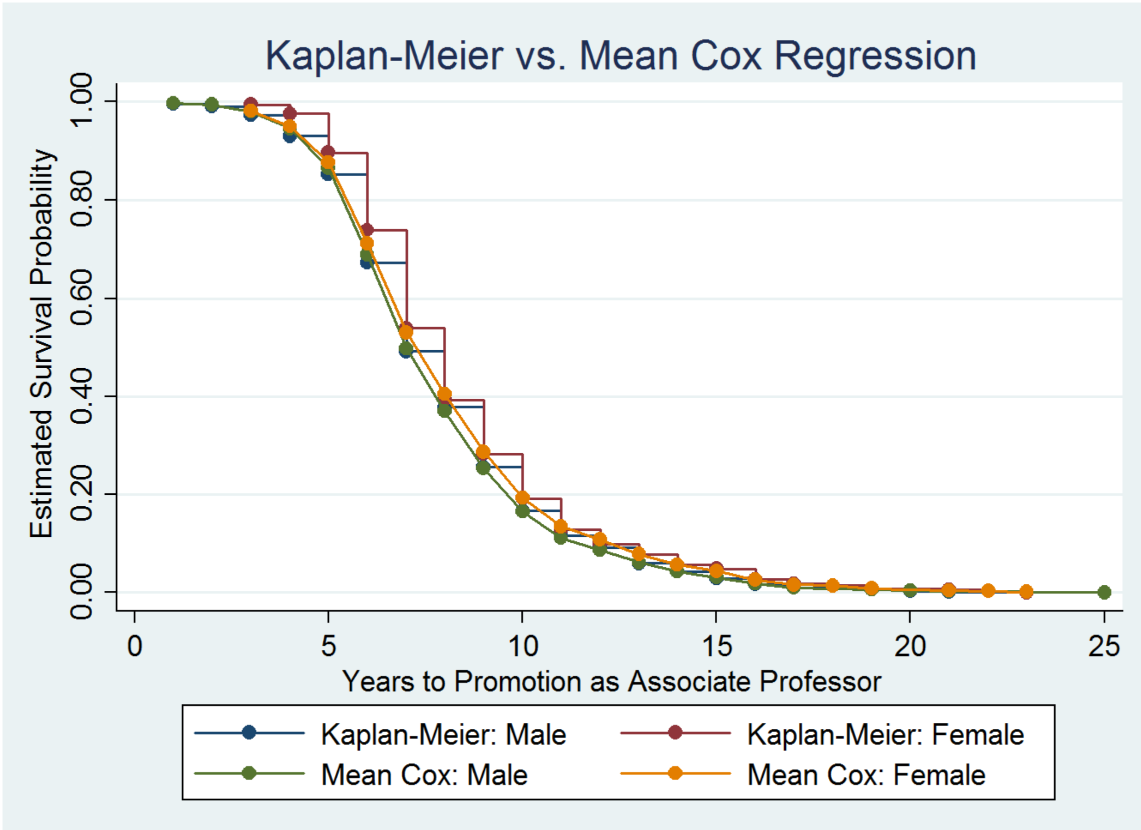

Figure 17. Plot of estimated survival probability vs. years to promotion as an associate professor. Smooth curves are Cox-regression mean adjusted survival estimates (predicted) and step curves are Kaplan-Meier survival estimates (observed). Males are shown in blue (observed) and green (predicted); females are shown in red (observed) and yellow (predicted).

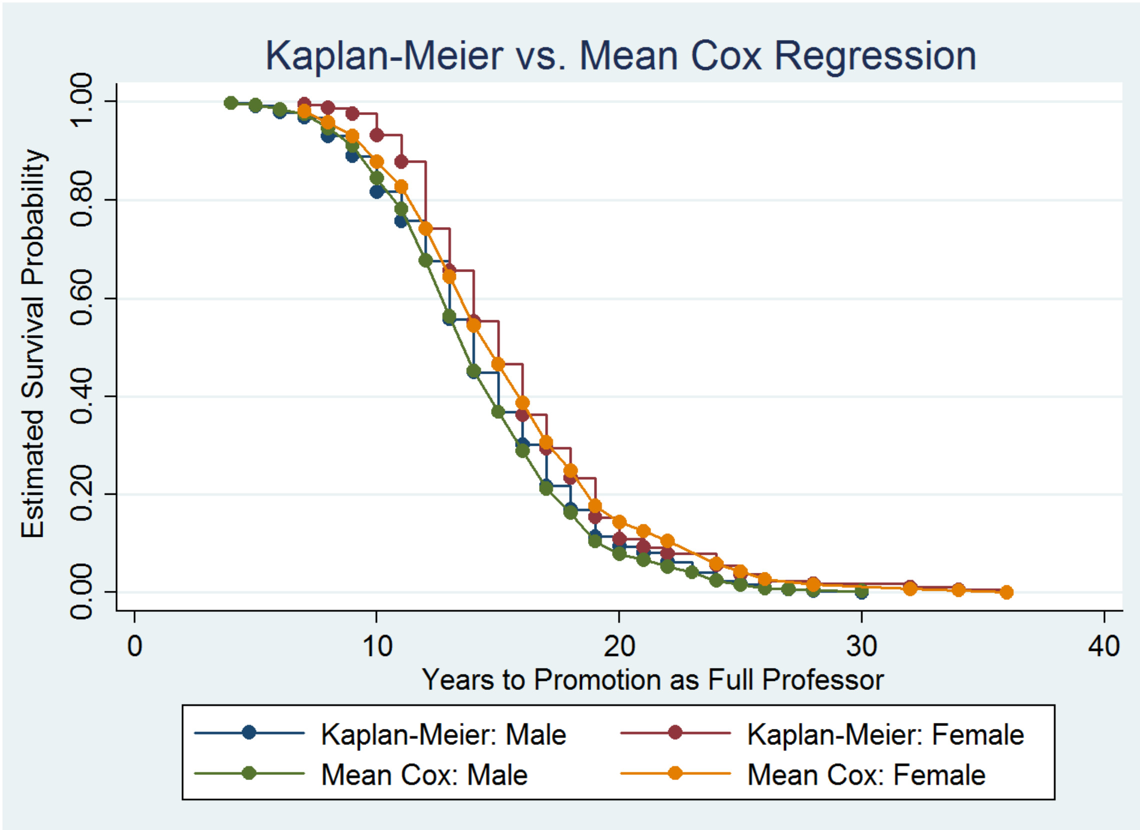

Figure 18. Plot of estimated survival probability vs. years to promotion as a full professor. Smooth curves are Cox-regression mean adjusted survival estimates (predicted) and step curves are Kaplan-Meier survival estimates (observed). Males are shown in blue (observed) and green (predicted); females are shown in red (observed) and yellow (predicted).

Generally the Cox adjusted survival curves, called Mean Cox in the graphs, are similar to the Kaplan-Meier survival curves, called Kaplan-Meier in the graphs, for male associate and full professors with observed and expected separating slightly before about 11 years for full professors. The female associate professor survival curves separate from about 4 to 8 years for associate professors and from about 16 to 22 years for full professors; in all cases Cox regression models using means of all covariates except gender are closer to the male values, and often closer for female values, than the uncorrected Kaplan-Meier survival estimates.

In addition to this visual comparison, it is possible to decompose the overall hazard ratios for associate professor promotion into hazard ratios for males and females for each variable using the mean of each of the covariates (see Table 35).

Table 35. Decomposition of Mean Adjusted Cox Regression Model Hazard Ratios for Associate Professors by Gender.

		Mean Values		Hazard Ratio	
Category	Variable	Male	Female	Variable	Category
	Gender	0	1	0.75	0.75
Experience	PhDHire (1)	4.18	3.60	1.82	1.11
	PhDHire (2)			0.61	
Productivity	HirePubs	1.99	1.09	0.86	0.93
	AscPPubs	13.40	10.74	1.11	
	CiteAscP	324.05	204.77	0.98	
Moves	Number	0.28	0.27	1.03	1.01
	To PhD granting	0.28	0.23	0.99	
Focus	Geography	0.63	0.64	1.01	1.01
	Human (% time)	23.78	24.18	1.00	
Overall					0.78

The results in Table 35 were calculated using the same coefficient for males and females and lists untransformed mean values for the variables to make the comparison easier. The gender coefficient reduced the rate of promotion for females by 25% compared to men. The rate that females were promoted increased by about 11% as a result of their being hired more quickly than men, PhDHire, and falls about 7% because females have fewer publications and citations than men. Publications have a mixed influence on promotion for females with publications when hired, HirePubs, reducing their rate of promotion by 14%, but with publications when promoted to become an associate professor, AscPPubs, increasing their rate of promotion by 11%. In both cases, HirePubs and AscPPubs, females have statistically significantly fewer publications with the gain in promotion for AscPPubs being due to its negative coefficient. Citations, differences in moves, and disciplinary focus have little effect on the rate of promotion for males or females. The mean adjusted Cox regression estimated survival curves are visibly closer for males and females than the Kaplan-Meier estimated survival curves, even though the difference in the overall hazard ratio is small, 22% vs. 25%, or 3%.

How much longer does it take females to become promoted in comparison to men? The mean number of years for females to be promoted is 8.51 years vs. 8.10 for men, a difference of 0.41 years or about 5 months; this difference is not statistically significant (see Table 16 in the APPENDIX). Why so little difference in time? The annual difference in survival probability, based on the Kaplan-Meier survival curves, was on average about 2%, and the average promotion rate was about 5% per year. An approximate calculation would be females lagged males on average by 2% and the average promotion rate was 5% per year, so females would be expected to lag males by about 2/5th of a year or about 5 months. Thus, a marked reduction in the promotion rate for females, 22% to 25%, translates into a 5 month slowing in the average time to promotion because the average rate of promotion is relatively small.

Table 36 shows a decomposition of the overall Cox regression model hazard ratios for male and female full professors using the means of their variables.

Table 36. Decomposition of Mean Adjusted Cox Regression Model Hazard Ratios for Full Professors by Gender.

		Mean Values		Hazard Ratio	
Category	Variable	Male	Female	Variable	Category
Experience	PhDHire	4.87	4.65	1.03	1.06
Productivity	HirePubs	1.80	0.94	1.04	0.92
	HireCites	47.76	18.00	0.88	
	CitAscP	327.85	209.76	1.02	
Race	White	0.81	0.81	1.00	1.00
Gender	Gender	0	1	0.91	0.91
PhD Cohort	< 1989	0.34	0.30	1.02	1.02
Overall					0.91

The results in Table 35 were calculated using coefficients from the stratified Cox regression model, which lacks a coefficient for the variable representing the cohort of PhDs granted before 1989, and lists untransformed mean values for ease of comparison. The rate of promotion for females is slowed by productivity and gender variables and aided by being hired a bit faster. Overall the promotion rate for female professors is about 9% slower than male professors; this is very similar to the 8% slowing estimated by the gender coefficient.

The mean number of years for females to be promoted is 15.7 vs. 14.5 for men, or 1.2 years longer; this difference is statistically significant (see Table 16 in the APPENDIX). How does a 8% to 9% slowing in the rate of promotion for females translate into a 1.2 year slowing in time? The annual difference in survival probability, based on the Kaplan-Meier survival curves, was on average about 5.5%, and the average promotion rate was about 4% per year. An approximate calculation would be females lagged males on average by 5% and the average promotion rate was 4% per year, so females would be expected to lag males by about 1.3 years. Thus, a 8% to 9% reduction in the promotion rate for females, translates into a 1.3 year slowing in the average time to promotion because the average promotion rate was only about 4%.

Females are clearly slower to be promoted than males and this might be partially be explained by their choice of research focus. The one research focus where there are an unexpected proportion of females is anthropology where 8.8% of females have this research focus vs. 1.9% for males (see Table 15 above). Is a research focus in anthropology associated with slowing of your rate of promotion to become an associate professor (see Figure 19)?

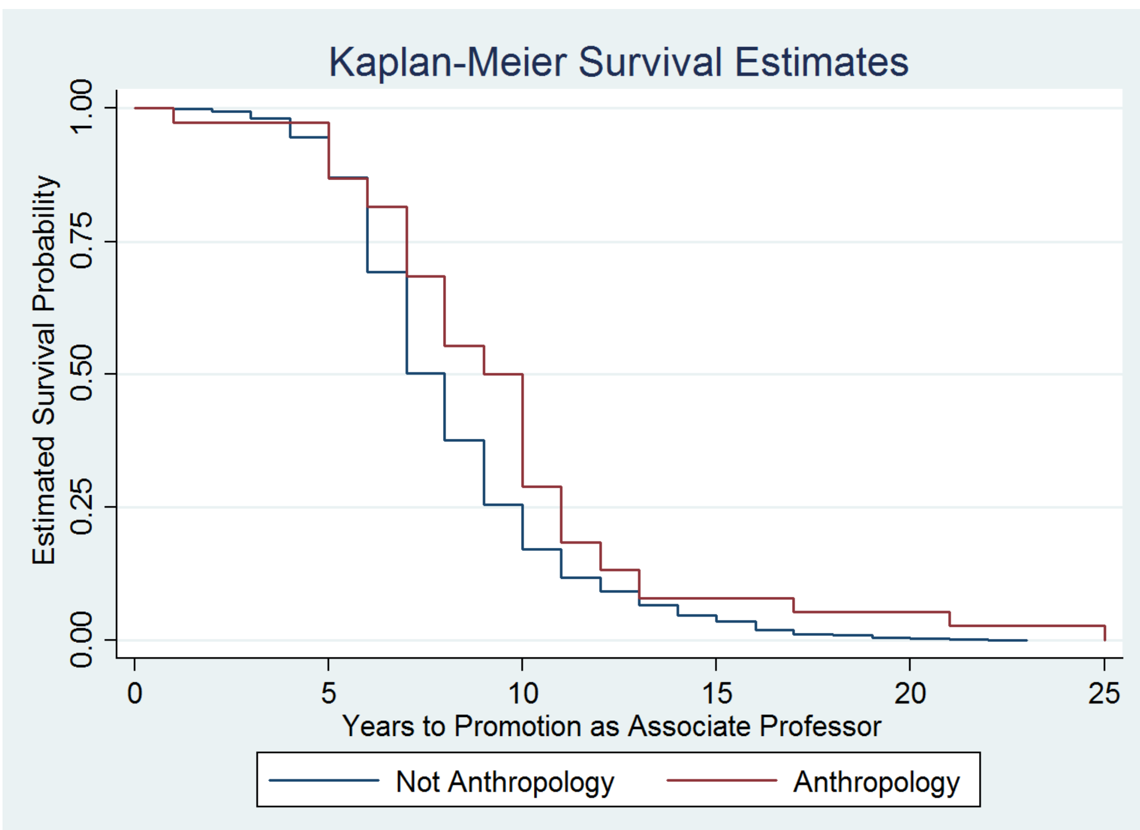

Figure 19. Plot of estimated survival probability vs. years to promoted as an associate professor. Professors with research focus in anthropology are shown in red and professors with other research interests are shown in blue.

As the Kaplan-Meier estimated survival curves show, professors with a research focus in anthropology are slower to be promoted (log rank test: $\chi^2 = 6.64$, df = 1, p = 0.01). On average a research focus in anthropology slows your promotion to become an associate professor from by about 3.1. This difference is statistically significant (t-test: t = 2.6388, df = 496, p = 0.0086, skewed distributions, Wilcoxon rank sum test: Z = 2.95, p = 0.0032). This analysis shows that choice of disciplinary focus may slow the rate of your promotion and is a partial answer to research question four.

Both Kaplan-Meier and mean adjusted Cox regression models show whites are slower to gain promotion to become full professors than other races (see Figure 20).

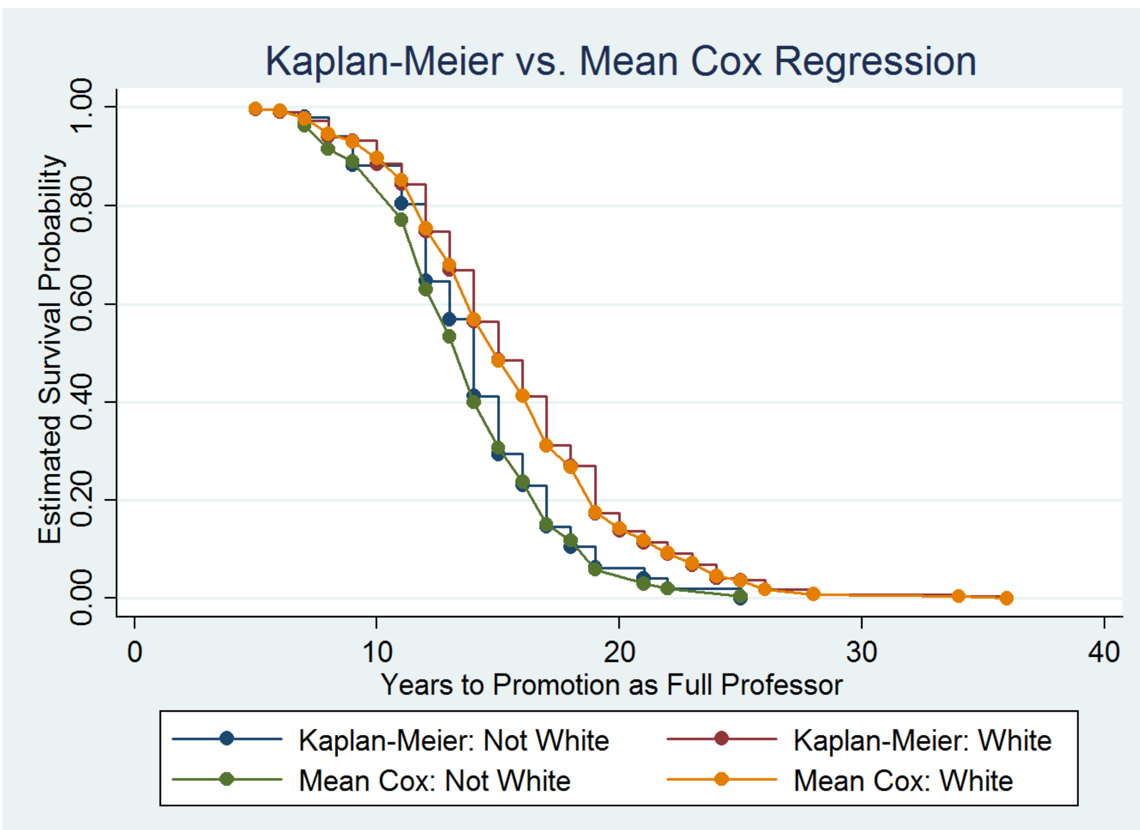

Figure 20. Plot of estimated survival probability vs. years until promoted as a full professor. Smooth curves are mean adjusted Cox regression survival estimates (predicted) and step curves are Kaplan-Meier survival estimates (observed). White race is shown in red (observed) and yellow (predicted); other races are shown in blue (observed) and green (predicted).

As Figure 20 shows the estimated survival curves, using Cox regression with covariates set to their mean values (except for white race) reveal whites lag other races variably; the two curves slowly diverge. The Kaplan-Meier survival curves were compared and were significantly different (log rank test: χ^2 = 7.68, df = 1, p = 0.0056). On average whites take 15.8 years to be promoted to full professor vs. other races taking 14.1 years (t-test: t = 2.41, df = 267, p = 0.0168; skewed distributions, Wilcoxon rank sum test, z = 2.44, p = 0.0149), or a difference of about 1.7 years. Comparisons of variables influencing promotion to a full professor in white and other races are shown in Table 37.

Table 37. Descriptive Statistical Differences between Whites and Other Races for Full Professors.

	White			Not White		
Variable	Mean	SD	N	Mean	SD	N
PhDHire*	5.34	6.67	218	4.76	5.79	50
HirePubs+	1.59	2.10	218	0.98	1.93	50
HireCits♦	41.9	101	218	13.9	41	50
CitAscP°	300	448	211	254	383	49
Gender∆	0.33	0.47	218	0.34	0.50	82
PhD<89⌂	0.53	0.48	377	0.26	0.39	82

* t-test: t = 0.5671, df = 266, p = 0.714, skewed, Wilcoxon rank-sum test: z = 0.132, p = 0.8953.
\+ t-test: t = 1.8722, df = 266, p = 0.0623, skewed, Wilcoxon rank-sum test: z = 2.381, p = 0.0173.
♦ t-test: t = 1.1916, df = 266, p = 0.0564, skewed, Wilcoxon rank-sum test: z = 2.647, p = 0.0081.
° t-test: t = 0.6569, df = 258, p = 0.5118, skewed, Wilxocoxon rank-sum test, z = 0.210, p = 0.8338.
∆ z =0.1317, p =0.8952.
⌂ z =3.4156, p =0.0006.

White full professors have more publications and citations when hired and are more likely to be part of the earliest PhD cohort, receiving their PhD before 1989, than are other races (see Table 35). Table 38 shows a decomposition of the overall Cox regression model hazard ratios for white and other races using the means of their variables.

Table 38. Decomposition of Mean Adjusted Cox Regression Model Hazard Ratios for Full Professors by Race.

		Mean Values		Hazard Ratio	
Category	Variable	White	Not White	Variable	Category
Years	PhDHire	5.34	4.76	1.01	1.01
Productivity	HirePubs	1.59	0.98	1.09	1.06
	HireCites	41.9	13.4	0.98	
	CitAscP	300	254	1.00	
Cohort	PhD<89	0.53	0.26	0.89	0.89
Race	White	1.00	0.00	0.65	0.65
Gender	Gender	0.33	0.34	1.00	1.00
Overall					0.62

The results in Table 38 were calculated using the coefficients from the Cox regression model and lists untransformed mean values for ease of comparison. The promotion rate for white professors is about 35% slower overall with most of the difference due to white race. White professors improve their chance of promotion about 6% by being more productive than professors of other races, but this is more than offset by being more likely to be in the cohort of PhD granted before 1989 which was promoted more slowly.

How does a 35% slowing in the rate of promotion for whites translate into a 1.7 year slowing in time? The annual difference in survival probability, based on the Kaplan-Meier survival curves, was on average about 10%, and the average promotion rate for whites and other races was about 6% per year. An approximate calculation would be whites lagged other races on average by 10% and the average promotion rate was 6% per year, so whites would be expected to lag other races by about 1.7 years. Thus, a 35% reduction in the promotion rate for females, translates into a 1.7 year slowing in the average time to promotion because the average promotion rate was only about 6% a year. Annual promotion rates were slower for whites and as a result whites would be expected to diverge from other races as seen. This extends the answer to the research questions to include showing an effect of race in addition to gender.

Whites are slower to be promoted, but what races are faster? As Figure 21 show Asians are faster to be promoted to become full professors than other races.

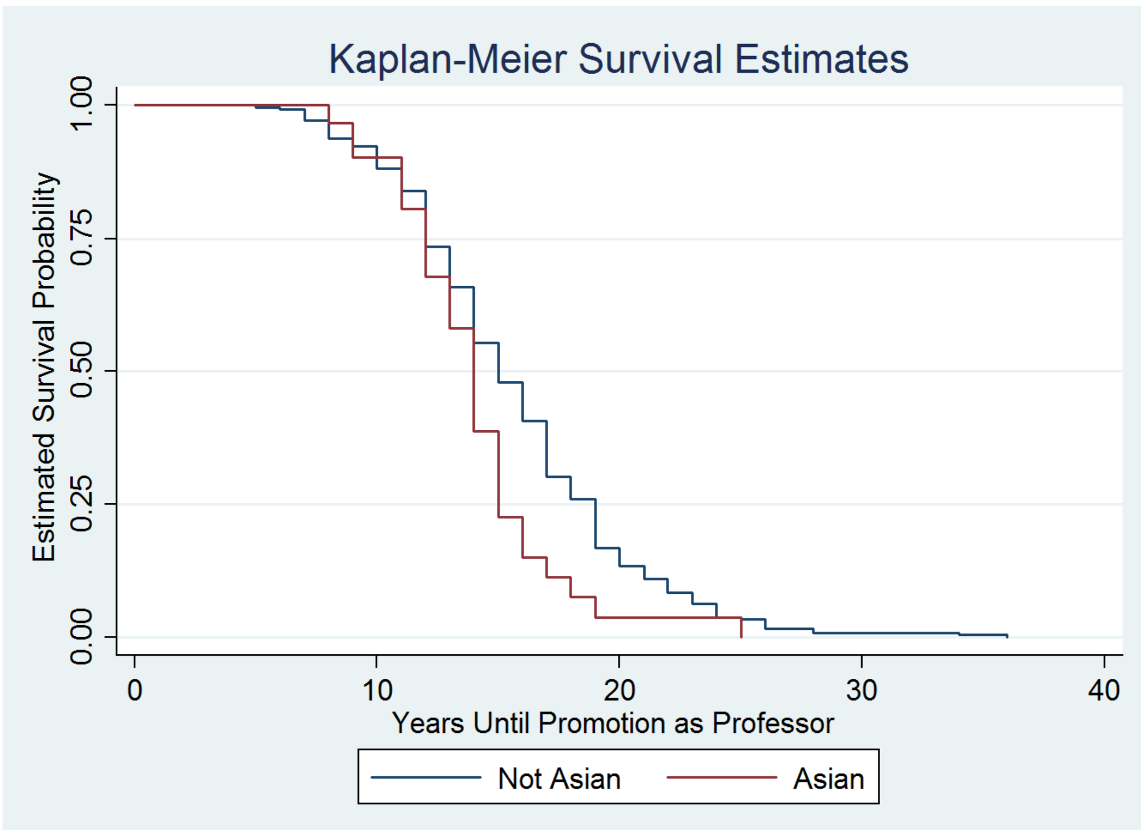

Figure 21. Plot of estimated survival probability vs. years until promoted as a full professor. Asians are shown in red and other races in blue.

The Kaplan-Meier survival curves were compared using the log rank test and the difference was significant (χ^2 = 5.96, df = 1, p = 0.0146). It is possible that Asians have skills which favor their hiring in a sub-discipline of geography, such as GIScience, where they spend more of their time than do other races: 38% vs. 15% for other races (t-test: t =

5.35, df = 453, $p < 0.00005$, skewed distribution, Wilcoxon rank sum test: $z = 5.744$, $p < 0.00005$). It appears that Asians are more rapidly promoted perhaps in part due to their choice of disciplinary focus, which is a partial answer to research question four.

4. DISCUSSION

This study has found that both gender and racial altered academic promotion. Females were slower to be promoted to become associate professors than males both as measured by Kaplan-Meier survival curves and by the average number of years needed to gain promotion, an 0.4 year difference. However, neither difference was statistically significant and females published fewer papers than males; this difference was statistically significant. Cox regression detected a significant gender coefficient even after correcting for publications and other variables. Further, when Cox regression was done using the mean values of males and females the degree of slowing in the rate of promotion was only reduced from 25% to 22%. Thus, the significant gender coefficient is not explained by a lack of productivity by females. Promotion of females to become full professors did not reveal a significant gender coefficient although women were slower to be promoted to become full professors and this difference was statistically significant. Thus, the results reject the null hypothesis, H_0, that: (1) females will be promoted to become full professors after the same amount of time as males (Hypothesis 1); (2) at a given time the proportion of females promoted to become full professors is less than that of males (Hypothesis 3); and (3) females are promoted to become associate and full professors at the same rate as males (Hypothesis 3).

An unexpected finding was that promotion to become full professors was slower for white and Asian professors than professors of other races. On average white professors were 1.7 years slower to become full professors than professors of other races; this difference was statistically significant. This difference occurred even though white professors were more productive as measured by publications. Cox regression revealed that white professors were about 35% slower to be promoted than professors of other races and this difference was not reduced when mean values for white professors and professors of other races were used. Thus, the results reject the null hypothesis, H_0, that: (1) whites will be promoted to become full professors after the same amount of time as other races (Hypothesis 1); (2) at a given time the proportion of whites promoted to become full professors is the same as that of other races (Hypothesis 2); (3) whites are promoted to become full professors at the same rate as other races (Hypothesis 3). Overall there is evidence of both gender and racial alter academic promotion. This study found statistical differences, which suggest an association but cannot prove causality.

Research focus and sub-discipline did affect the rate of promotion with anthropology faculty being slower to be promoted to become associate professors and suggestive evidence that Asians are more rapidly promoted to become full professors because of their focus on GIScience. These results reject the null hypothesis, H_0, that promotion is independent of research focus and sub-discipline (Hypothesis 4). The one hypothesis that was confirmed (Hypothesis 5) was that the regional distribution of geography faculty at PhD-granting institutions did not vary by gender.

When looking for differences in academic promotion associated with race or gender, why choose geography? First, geography is a remarkably diverse discipline spanning the natural sciences; such as geology, computer science, and environmental science; as well as the social sciences; such as anthropology, economics, and sociology (Foote and Solem 2009, 49). PhD-granting geography departments also span the United States permitting this study to include 74 institutions in 36 states. Further, other studies have interpreted their findings as evidence of gender discrimination in academic promotion. This is true in disciplines such as economics (Ginther and Kahn 2004, 201-203), mathematics (Long 2001, 37-39), and philosophy (Bishop, et al. 2013, 245) where relatively few females have received their PhDs: economics 24% (Holden 1996, 1919), mathematics 21%, and philosophy 29% (Bishop, et al. 2013, 247). Note the percentage for geography is about 24% (Holden 1996, 1919). These are the same disciplines where relatively few females are promoted to high academic ranks: females are less than 10% of full professors in economics in 2003 (Ginther and Kahn 2004, 196), 28% of full professors in mathematics in 1995 (Long 2001, 296), and 18% are full professors in physical geography in 1996 (Luzzadder-Beach and Macfarlane 2000, 410-412). Further, the institutions most likely to discriminate in academic promotion are PhD-granting institutions (Bayer 1973, 23; Long 2001, 166, 172; Marschke, et al. 2007, 4). This evidence suggests that PhD-granting departments of geography are likely to show evidence of gender differences in academic promotion.

An ideal study of gender differences in academic promotion would involve randomly assigning male and female assistant professors to a given institution and then following them over time to see when they were promoted (Rothman, Greenland, and Lash 2008, 88-92; Spector 1981, 7-8). Obviously this type of study is impossible (Juni, Altman, and Egger 2001, 42; Rothman, Greenland, and Lash 2008, 88-92), so what factors should be incorporated into the research design? One obvious factor is time. Cross-sectional studies, which survey professors and record their academic ranks, ignore the importance of time (Menard 2002, 2). Current full professors reflect hiring conditions many years before the study, so a study should compare professors hired at about the same time (Menard 2002, 2-4). Even better would be to match professors according when their PhD was granted and the institution which hired them as assistant professors (Rothman, Greenland, and Lash 2008, 174-175). A potential advantage of a matched cohort design is a reduction of the effect of unmeasured variables on the chance that an assistant professor would be promoted (Rothman, Greenland, and Lash 2008, 174-175). A potential limitation of a matched cohort design is that it is less representative of population of professors studied (Long 2001, 25), although in this study the proportion of females in the total population and matched cohort only differed by 2% which was not statistically significant.

One of the main goals of studies of the influence of gender and race on academic promotion is to identify variables which predict academic promotion, a binary event, which occurs years after an assistant professor is hired. Linear regression accommodates independent variables, such as number of publications, but does not accommodate a binary dependent variable, such as promotion (Meyers, Gamst, and Guarino 2006, 148). Logistic regression accommodates independent variables and a binary dependent variable, but does not incorporate time to an event, such as years to promotion (Meyers, Gamst, and Guarino 2006, 222). The obvious advantage of Cox regression is that, in addition to accommodating independent variables, it is designed for a binary outcome which occurs as a function of time (Hosmer, Lemeshow, and May 2008, 1-2). One problem with collecting data about academic promotion is that some assistant professors would be expected to leave without being promoted or be promoted after the study period ended; this would generate right-censored data (Hosmer, Lemeshow, and May 2008, 7). An important advantage of Cox regression is that it is designed for situations where censored data is expected (Klein and Moeschberger 2003, 63-72; Kleinbaum and Klein 2005, 4-7). For cohorts of PhDs or assistant professors, right-censored data would be expected, so survival analysis is the appropriate method of analysis.

Matched cohorts would be expected to be similar, but male and female faculty had some distinctive features. Despite matching of males and females, more females were found in the most recent cohort of PhDs, those granted after 1997. Females were more likely to receive their PhD from a top-ranked program than men, 38% vs. 29%. Despite this advantage females published fewer papers and were cited less than males at each step of their career: (1) when hired as an assistant professor; (2) when promoted to become an associate professor; and (3) when promoted to become a full professor. This difference might be due to males spending more time doing research than females, as well as more total hours working. Males were more likely than females to focus on GIScience and physical geography; more females than males to focus on anthropology. Marital status varies with females being more likely to be single and less likely to be married than men. Married females were more likely to have a spouse working full-time; the spouse or partner of a married man was more likely not to work than that of a married woman. The number and timing of children were the same in female and male faculty who have children. Females were more likely to have their job search restricted geographically than males and more likely to vote for Democratic candidates than men. Other variables, such as race, were equally matched in male and female professors.

Demographic variables in this study were similar to those in the literature with white males dominating (Bayer 1973, 14; Nettles, Perna, and Bradburn 2000, 25) and Asians being the second largest group (Nettles, Perna, and Bradburn 2000, 29). Kulis and Sicotte (2002, 12) reported that female faculty favor the northeast and west coast, but no gender difference in the regional distribution of male and female geography faculty was detected in this study. The proportion of foreign born geography faculty is about 30% and a bit larger than the 17%-27% reported in other studies (Ginther and Hayes 2003, 39; Ginther and Kahn 2004, 200; Ginther and Kahn 2006, 24). When male and female geography faculty were compared, none of these demographic differences were statistically significant.

At work male and female geography faculty did differ. Females were more likely than males to have received their PhDs from top ranked geography programs, but were equally likely to be employed at a top ranked institution. The results in the literature are quite variable with no consistent difference between males and females in their receipt of a PhD from or employment by a top ranked institution (Ginther and Kahn 2006, 24; Long, Allison, and McGinnis 1993, 710). It took both male and female faculty about four years on average after they received their PhD before they were hired as an assistant professor at a PhD-granting institution. Inbreeding, or being hired as an assistant professor by the institution which granted your PhD, was uncommon, about 5% in geography, and similar to the 6% to 20% rate noted in the literature (Ginther 2001, 9; Long, Allison, and McGinnis 1993, 711). In terms of work hours, male geography faculty worked a few more total hours and devoted more time to research than females; females and males spent about the same time teaching. This result is similar to previous reports which find males spend more time in research, but unlike this study find females spend more time teaching (Bayer 1973; Manchester and Barbezat 2013, 61; Nettles, Perna, and Bradburn 2000. 91-95; Winslow 2010, 779; Xie and Shauman 1998, 865-

868). This study found that males and females were equally likely to move; the literature has been inconsistent on this point (Ginther and Kahn 2006, 24; McElrath 1992, 274; Rosenfeld and Jones 1987, 501).

A near universal finding in the literature is that male publish more than female faculty (Astin 1972, 378; Bayer 1973; Ceci et al. 2014, 103-105; Cole and Zuckerman 1984, 224; Fox 2005, 135; Fox and Faver 1985, 542; Ginther and Kahn 2006, 24, Hesli, Lee, and Mitchell 2012, 478; Levin and Stephan 1998, 1056; Nettles, Perna, and Bradburn 2000, 29; Xie and Shauman 1998, 856). This study found males published and were cited more than female faculty at each step of their career; other studies have not found a difference in citations (Ginther and Kahn 2004, 200, 202; Long, Allison, and McGinnis 1993, 710-711). Long, Allison, and McGinnis (1993, 710-716) found that females had more papers when hired than men, but did not differ in the number of citations. This study found no difference in the amount of grant funding that male and female professors reported; other studies report males receive more funding (Bayer 1973; Ferber and Green 1984, 558; Nettles, Perna, and Bradburn 2000, 8, 40).

Like other studies in the literature, this study found that males are more likely to be married (Astin and Milem 1997, 131, 143; Bayer 1973; Fox and Faver 1985, 542; Ginther 2001, 8; Ginther and Hayes 2003, 40; Goulden, Mason, and Frasch. 2011, 151; Hesli, Lee, and Mitchell 2012, 479; Long, Allison, and McGinnis 1993, 710; Mason and Goulden 2004, 92; Rudd et al. 2008, 232-233) and that the spouses of females were more likely to work full-time (Bayer 1973; Jacobs and Winslow 2004, 155; Macfarland and Luzzadder-Beach 1998, 1612; Rudd et al. 2008, 233). Unlike most studies in the literature this study found no difference between males and females in the number or timing of their children (Fox and Faver 1985, 542; Ginther and Hays 2003, 40; Ginther and Kahn 2006, 24; Goulden, Mason, and Frasch. 2011, 151; Hargens, McCann, and Reskin 1978, 158; Jacobs and Winslow 2004, 153; Long, Allison, and McGinnis 1993, 710; Mason and Goulden 2004, 92; Perna 2005, 288; Sax et al. 2002, 441; Stack 2004, 917). Females were more likely to report that their job search was limited geographically than men; other studies also found this result (Kulis and Sicotte 2002, 15; Luzzadder-Beach and Macfarlane 2000, 419-420; Marwell, Rosenfeld, and Spilerman 1979, 1226-1228)

Cox regression was used to identify potential variables which had significant univariate p-values. For associate professors the most significant predictors were publications and citations, but also a focus on geography in general and human geography in particular. In addition, moves as an associate professor, both the total number of moves and moves to PhD-granting institutions, were significant predictors. The years between the granting of their PhD and being hired as an assistant professor, or PhDHire, turned out to have a complex relationship with promotion. A small number of professors were hired before they received their PhDs and were promoted more rapidly. Another group of professors were hired more than 15 years after receiving their PhD; they too were promoted a little more rapidly. For associate professors, gender had a relatively insignificant univariate p-value of 0.16.

The variables favoring promotion to become a full professor were cumulative publications when hired as an assistant professor and citations, but also gender and white race. Publications and citations at the time an assistant professor was hired had more significant p-values than publications or citations later in a professor's career. Excluding publications when hired as an assistant professor, citations predicted promotion better than publications. As with associate professors, the years between completion of a PhD and hiring as an assistant professor were a highly significant univariate predictor.

Some variables were missing from the list of highly significant univariate predictors. Promotion was similar in the geographic regions tested and the number of hours spent working and their distribution were not strong predictors. Neither marital status nor children favored or hindered promotion. Other variables influenced promotion differently with advancing rank. Moves as an assistant professor favored promotion to become an associate professor, but were not significant for promotion to become a full professor. Promotion to become a full professor depended more on citations than promotion to become an associate professor which depended more on publications.

This study and the literature agree that publications increase the chance of promotion (Astin and Bayer 1972, 106-108; Ferber and Green 1982, 563; Ginther and Hayes 2003, 52; Ginther and Kahn 2004, 202; Ginther and Kahn 2006, 37; Hesli, Lee, and Mitchell 2012, 480-482; Long, Allison, and McGinnis 1993, 711; McElrath 1992, 275). What is different in this study is that publications or citations when hired are significant in predicting promotion to become an associate or full professor. If reproducible, this finding might aid departments in selecting which PhDs to hire as assistant professors and might provide guidance for PhDs in evaluating their chance of being hired. Moves made as an assistant professor, both the number and moves to PhD-granting institutions, altered the rate of promotion to become an associate professor. Moves as an assistant professor reduced the chance of promotion to become an associate professor in this study and in the literature (Ginther and Kahn 2006, 36; Long, Allison, and McGinnis 1993, 711; McElrath 1992, 275; Rosenfeld and Jones 1987, 509). This study found a complex relationship between the number of years between the granting of their PhD and hiring as an assistant professor. The complex relationship reflects different groups of assistant professors with some assistant professors hired before they received their PhD; this favored more rapid promotion. Another group of assistant professors were hired more than 15 years after receiving their PhD; this group also was promoted a little more rapidly to become associate professors. Other studies have not reported this complex relationship. For promotion to full professor, white race had a negative effect, which was highly significant, large in magnitude, and not mentioned in the studies reviewed. Evidence of different treatment of females confirms many studies in the literature (Ahern and Scott 1981, xv; CEEWISE 1979, 118; Ginther 2001, 5-8; Ginther and Hayes 2003, 36-38; Ginther and Kahn 2004, 197-199; Hesli, Lee, and Mitchell 2012, 490; Kaminski and Geisler 2012, 865; Long, Allison, and McGinnis 1993, 711; Long 2001, 219; Nettles, Perna, and Bradburn 2000, 6, 29; Perna 2001, 550; Roos and Gatta 2009, 183); evidence of different treatment of the white race may be novel.

The effect of gender on promotion varied with academic rank: (1) gender was associated with a large, 25%, and statistically significant reduction in the rate of promotion of females to become associate professors; and (2) a smaller, 8%, and statistically insignificant reduction in the rate of promotion of females to become full professors. Other than gender, productivity variables most strongly predicted promotion; here females were at a disadvantage of 7% to 11% in their rate of promotion because they published fewer papers and were cited less. Based on mean adjusted Cox model hazard ratios females were 22% slower to be promoted to become associate professors and 8%

slower to become full professors. Slower rates of promotion should increase the time it takes females to be promoted.

How much slower in time were females to be promoted to become associate or full professors? On average females were about 5 months slower to be promoted to become associate professors and about 1.2 years slower to be promoted to become full professors. This small difference in time was not statistically significant when Kaplan-Meier survival curves were compared for associate professor promotion, although the difference for full professor survival curves was statistically significant.

How can such large, 14% to 25%, reductions in the promotion rates for females cause such relatively small differences in time to promotion? The reason is that the annual rate of promotion, based on Kaplan-Meier survival curves, was only 4% to 5% per year and the average difference in the survival curves for associate professors was about 2% and 5% for full professors. These average differences give estimates close to those observed in the Kaplan-Meier survival curves: (1) female associate professors lag males on average by 2% with an average promotion rate of 5% per year giving an estimated slowing of 0.4 years or 5 months; and (2) female full professors lag males on average by 5% with an average promotion rate of 4% per year giving an estimated slowing of 1.25 years. Obviously the actual hazard rate calculation is a derivative and not an average rate of change, but the average estimate is reasonably close to the observed result. Large differences in the rate of promotion of females translate into relatively small differences in the time to promotion because the difference between the survival curves for males and females is small relative to the promotion rate.

Cox regression models can be adjusted by using the model's coefficients and mean values of the covariates, and then compared for male and female professors. This analysis permits the identification of factors in promotion to become an associate professor which distinguish between males and females. Using the mean adjusted Cox regression model, only three factors, which strongly predict promotion to become an associate professor, differed between males and females in their effect on promotion: (1) gender; (2) years between receiving their PhD and hiring (PhDHire); and (3) cumulative publications when hired as an assistant professor (HirePubs). All of these variables are known when an assistant professor is hired. The Association of American Geographers Directory lists the number of PhDs granted in a given year with the average between 1991 and 2007 being 174 with an average of 33 assistant professors being hired by PhD-granting institutions each year. Thus, the ratio of PhDs to assistant-professor positions is about five PhDs. Collectively, this suggests that departments of geography only hire assistant professors who are very likely to be promoted. Supporting this speculation is the negative coefficient for cumulative publications when promoted to become an associate professor. This seems paradoxical: If promotion is a reward for productivity while an associate professor, then cumulative publications should favor promotion of the more productive professors and not penalize them. Males are well known to publish more than females (Astin 1972, 378; Bayer 1973; Ceci et al. 2014, 103-105; Cole and Zuckerman 1984, 224; Fox 2005, 135; Fox and Faver 1985, 542; Ginther and Kahn 2006, 24, Hesli, Lee, and Mitchell 2012, 478; Levin and Stephan 1998, 1056; Nettles, Perna, and Bradburn 2000, 29; Xie and Shauman 1998, 856), so a negative coefficient means females are promoted more rapidly as a result of publishing less than men. Why a penalty for productivity? Departments may be encouraged to make promotion decisions after an assistant professor has served a certain number of years (Hilmer and Hilmer 2010, 354); this "tenure clock" would require that the promotion of males be slowed a bit relative to females, since males publish more. Affirmative action plans would also encourage the promotion of female faculty. The mean-adjusted Cox regression model does include other significant predictors, such as number of moves and sub-disciplinary focus, but none actually influences the rate of promotion by more than 1%.

Promotion to become a full professor, based on the stratified Cox regression models, also depends on factors known when an assistant professor is hired: (1) gender; (2) cumulative publications when hired as an assistant professor (HirePubs); and (3) years between receiving their PhD and hiring as an assistant professor (PhDHire). These are the same factors favoring promotion to become an associate professor. The main difference is that citations are more important for promotion to become a full professor and females are slowed in their promotion to become full professors relative to males by 12% due to their lack citations when hired. Promotion to become a full professor takes many years. During this time papers published before being hired as an assistant professor have had time to be cited in the literature and their relative importance assessed. This may explain why citations are more important: they are a measure of a reputation in the community of scholars (Landes and Posner 2000, 321).

If departments can identify PhDs who are very likely to be promoted to become associate professors, then it is likely that the supply of PhDs is large relative to the hiring demand. If true then an investigation of the supply and demand conditions driving hiring is worthy of further study. This study did identify some sub-disciplines where promotion rates varied: anthropology and GIScience. This suggests that a study of whether market fragmentation exists with supply and demand varying by specialty within geography. Where are market conditions best for PhDs or departments? If promotion is determined when an assistant professor is hired, then further study of the factors favoring hiring would be a productive next step.

This study was not designed to look for differences in academic promotion associated with race. The only race capable of meeting the $\geq$ 10 events per variable criterion for inclusion in a Cox regression model was the white race and white race was only entered into the Cox regression model for full professors, where it was significant in all models. The effect of white race on promotion to become a full professor was similar to that of gender on the rate of promotion to become an associate professor in that: (1) the slowing in the rate of promotion, estimated by hazard ratios, was similar; (2) adjusting the Cox regression model by including the mean values of the covariates only changed the slowing of the rate of promotion very little; (3) differences in productivity between males and females or whites and other races had a relatively small effect in the adjusted Cox regression model; and (4) the actual slowing in years was similar. Overall the evidence of differences in academic promotion associated with white race appears to be as strong as that with females.

Under the law racial discrimination does not require minority status and potentially could apply to majorities, such as the white race, where it is called reverse discrimination. Evidence that blacks and females are discriminated against has been presented in several papers (Ginther 2001, 22-23; Ginther and Hayes 2003, 55-59;

Ginther and Kahn 2004, 205-206; Kramer 2001, 1), but the possibility that whites might be discriminated against has received little attention and is worthy of further study.

Research and subdisciplinary focus may be an important factor in academic promotion. Academic promotion is slowed by a research focus on anthropology but is favored by a subdisciplinary focus on GIScience. This raises the possibility that supply and demand may vary within the markets for professors with a specific research and subdisciplinary interest. A successful department of geography may need a diverse faculty as measured by their research and subdisciplinary interests to compete for resources, students, and external funding. The narrow lens of discrimination may exclude wider market and competitive forces interacting with promotion decisions.

Regression coefficients, like other forms of circumstantial evidence, have limitations. They suggest, but do not prove, discriminatory intent. Further, the method used to select variables fails to have a separate dataset to confirm the accuracy of the variables selected. A typical limitation of using data-driven methods to select variables is that they are biased to select weak predictors (Miller 2002, 165; Royston and Sauerbrei 2008, 40, 48). In an attempt to reduce the bias favoring the selection of weak predictors, this study favored a parsimonious and simple regression model. A parsimonious regression model includes all the strong predictors, but for associate professor promotion did not include gender, which was forced into the model; for full professor promotion both gender and white race variable were highly statistically significant and automatically included in the model. Once in the regression model, gender became highly significant in the associate professor promotion model and white race continued to be highly significant in the full professor model.

Could the Cox regression model lack key variables which predict promotion of white professors and would cause the white-race variable to become insignificant (Paetzold and Wilborn 2012, 290)? There is an extensive literature on variables associated with gender discrimination in academic promotion; these variables were screened for inclusion in the Cox regression model used. Are there variables which specifically predict discrimination against the white race? These variables have not been studied, which creates another opportunity for further investigation.

Some possible areas of future research would include confirming the basic findings of this research in other disciplines. Ideally it would be useful to have more data on grant and contract funding than was possible in this study. For example the source of funding, such as the National Science Foundation, may be important. Further, ranking the quality of publications may add new information. A possible measure of a professor's teaching productivity might be the number of graduate students a professor mentored and the productivity of his students. Research on these variables might explain some of the difference in the rate of promotion seen.

In this study both gender and racial are associated with slowing of the rate of academic promotion by as much as 25% to 30%. However, the actual slowing in time is relatively slight, 0.4 years for females to be promoted to become associate professor and 1.7 years for whites to become full professors. Even if there is clear evidence of statistical significance, are the damages significant (Paetzold and Wilborn 2012, 290-291)? The law usually calculates economic damages by estimating the loss in salary (Anonymous 1933, 1256). How much salary was lost? Each year the American Association of University Professors lists the salaries of university professors working at PhD-granting institutions (Barnshaw and Dunietz 2015). The median salaries in 2015 were about: (1) $76,000 for assistant professors; (2) $88,000 for associate professors; and (3) $128,000 for full professors at PhD-granting institutions (Barnshaw and Dunietz 2015). The estimated damages from slowed promotion are shown in Table 39.

Table 39. Economic Damages from Slowed Promotion Associated with Gender and Race

Group	Promotion Delay (years)	Academic Rank	Number	Lost Salary per Year	Lost Salary	Total Damages
Females	0.4	Associate	330	$12,000	$4,800	$1,584,000
White	1.7	Full	220	$40,000	$68,000	$14,960,000

The damages for slowed promotion are significant, with each woman professor losing $4,400 and each white professor losing $69,000. This study included about 330 females who became associate professors and about 220 whites who became full professors. This gives total economic damages of over $15,000,000. This suggests that the damages are significant.

How could a powerful and dominant majority, white full professors, be treated differently than other races? Under the law, there is a potential conflict between affirmative action and reverse discrimination (Flygare 1984, 500; Schwartz 2000, 689). Federal law requires affirmative action plans whose goal is to increase the diversity of faculty working in universities. If affirmative action plans are acted upon then non-white faculty would be promoted a bit faster than white faculty, producing more quickly the desired result of a more diverse senior faculty. A side effect is that it could also save universities a significant amount of money, as outlined in Table 38 above. Since many universities face constrained budgets (Jenkins 1988, 12) and salaries are the dominant cost of running a university (Firmin et al. 1968, 124), this would be an attractive result. However, this financial gain could be erased if evidence of slowing of the rate of promotion of white full professors emerges from other disciplines; this would increase the risk that universities would have to defend against reverse discrimination lawsuits (Flygare 1984, 500; Schwartz 2000, 689). Of course, the results found in geography may be an aberration, but this speculative hypothesis needs to be tested in other disciplines.

Given the combination of: (1) statistical evidence of differences in academic promotion associated with gender and race and (2) significant economic damages, is litigation a remedy? As a practical matter, most claims of discrimination in academic promotion by a professor against their department or university are futile (Hora 2001, 356; West 1994, 124-125; White 2010, 842). A professor seeking to assert a claim of gender or racial discrimination in academic promotion faces as series of problems: (1) who had the intent to discriminate; (2) judicial deference to academic freedom; (3) the subjective nature of promotion decisions; and (4) the subconscious nature of bias (West 1994, 124-125). As an example, academic promotion often involves more than one committee, so who actually made the decision? Is circumstantial evidence of intent to discriminate by one member of one committee adequate? As long as there is evidence suggesting either gender or racial discrimination in academic promotion, then academic institutions should attempt to make the promotion process open, fair, and transparent. Further, assistant professors should have enough mentoring so the "rules of the game" are obvious.

Statistical evidence of differences in academic promotion associated with gender and race suggests that the slow erosion of support for affirmative action is premature. But what sort of affirmative action is appropriate? Strong affirmative action where gender or race is used to directly increase the probability of promotion, by say giving points for race or gender, would be viewed as unethical (Kekes 1993, 156; Markie 1993, 284). Weaker forms of affirmative action, such open access to information and fair procedures, are likely to be supported by all and viewed by most as already in place. Thus, weak forms of affirmative action are probably already reflected in this study and strong forms of affirmative action would be resisted by many. Perhaps the simplest idea would be to audit current affirmative action plans to see if they have been implemented as desired. If audits revealed evidence that affirmative action plans were not being implemented appropriately, then notice would be given to the university and negotiation started with the goal of improving the effectiveness of the university's affirmative action plan. If universities were hesitant to act then communication of their deficiencies to rating agencies or the press could be considered or a reduction in federal funds sought via litigation (Anonymous 1980, 608-609).

APPENDIX SECTION

Survey Documents

1. Prenotice Letter

TEXAS STATE UNIVERSITY
SAN MARCOS
The rising STAR *of Texas*

(Date)

(Address)

Dear Professor X:

I invite you to take part in a study being conducted by the Department of Geography at Texas State University investigating how faculty are hired and promoted. In a few days you will receive a questionnaire designed to collect information which will aid in the identification of some of the important factors. This study will only succeed with your generous help. You will be given a small token of our thanks with your request to participate in this study.

Best Wishes,

J. Pickett
PhD Student

DEPARTMENT OF GEOGRAPHY
601 UNIVERSITY DRIVE | SAN MARCOS, TEXAS 78666-4616 | *phone* 512.245.2170 | *fax* 512.245.8353 | WWW.TXSTATE.EDU

2. Survey Cover Letter

Texas State University-San Marcos, founded in 1899, is a member of The Texas State University System.

TEXAS STATE UNIVERSITY
SAN MARCOS
The rising STAR of Texas

(Date)

(Address)

Dear Professor X:

As a member of the academic profession, you are involved in the process of the academic hiring and promotion, and for that reason we invite you to take part in our study on the hiring and promotion process for geography faculties. By filling out the enclosed questionnaire you will help us discover some of the factors which influence hiring and promotion.

The questionnaire is brief with only 15 questions. Your participation is voluntary and confidential. If you have any questions about the study or this questionnaire please contact me at the address below or by e-mail at JP1647@txstate.edu. This study is supervised by Professor Yongmei Lu. The Institutional Review Board of Texas State University has reviewed and approved this study. If you have questions about your rights as a participant in this study you may contact them at (512) 245-2314.

By investing only about 20 minutes of your time, you will help us to complete this important research project. Please accept the enclosed small token of our appreciation as our thanks for your participation. We look forward to your responses.

Many Thanks,

J. Pickett
PhD Student

DEPARTMENT OF GEOGRAPHY
601 UNIVERSITY DRIVE | SAN MARCOS, TEXAS 78666-4616 | *phone* 512.245.2170 | *fax* 512.245.8353 | WWW.TXSTATE.EDU

3. Thank You Postcard

Front

(Date)
Last week we mailed a questionnaire to you because you are a faculty member who has been involved in the process of academic hiring and promotion.

If you have completed and returned the questionnaire, please accept our sincere thanks. If not, please do so right away. We are especially grateful for your help with this important study.

If you did not receive a questionnaire, or if it was misplaced, please e-mail me at JP1647@txstate.edu and I'll get another one in the mail today.

Sincerely,

Department of Geography

J. Pickett
PhD Student

(Address)

Back

TEXAS STATE UNIVERSITY
SAN MARCOS
The rising STAR *of Texas*

4. Replacement Questionnaire Cover Letter

TEXAS STATE UNIVERSITY
SAN MARCOS
The rising STAR of Texas

(Date)

(Address)

Dear Professor X:

A few weeks ago we sent a letter to your address inviting you to fill out a questionnaire about academic hiring and promotion. Up until this date, we have not received your finished questionnaire yet.

We are writing again as your response to the questionnaire is important if we are to accurately identify which factors most influence academic hiring and promotion. By now we have heard from most of our sample, but our ability to detect meaningful differences depends on the number of surveys completed. Quickly filling out the enclosed questionnaire and returning it will help us successfully complete this study.

The questionnaire is brief and should only take about 20 minutes to fill out. Your participation is voluntary and confidential. If you have any questions about the study please contact me at the address below or by e-mail at JP1647@txstate.edu. This study is supervised by Professor Yongmei Lu. The Institutional Review Board of Texas State University has reviewed and approved this study and if you have questions about your rights as a participant in this study you may contact them at (512) 245-2314.

We are looking forward to receiving your response.

Sincerely,

J. Pickett
PhD Student

Department of Geography
601 University Drive | San Marcos, Texas 78666-4616 | *phone* 512.245.2170 | *fax* 512.245.8353 | www.txstate.edu

Texas State University-San Marcos, founded in 1899, is a member of The Texas State University System.

5. E-Mail Cover Message

Subject: Academic Hiring and Promotion Survey

< Date >

Dear Professor X:

A few weeks ago we sent a letter to your address inviting you to fill out a questionnaire about academic hiring and promotion, but have not received your response. Your response to this brief questionnaire is important. To aid in the completion of this study, I have attached a fillable PDF which you can fill out and return to JP1647@txstate.edu.

Your participation is voluntary and confidential. If you have any questions about this study please contact me at the address below or by e-mail at JP1647@txstate.edu. This study is supervised by Professor Yongmei Lu. The Institutional Review Board of Texas State University has reviewed and approved this study and if you have questions about your rights as a participant in this study you may contact them at (512) 245-2314. Thanks for quickly filling out the questionnaire.

Sincerely,

J. Pickett
PhD Student

6. IRB Approval E-Mail

Friday, January 25, 2013 3:29 PM

This email message is generated by the IRB online application program. Do not reply.

The reviewers have determined that your IRB Application Number 2012C2735 is exempt from IRB review. The project is approved.

If you have questions, please submit an IRB Inquiry form at:
http://www.txstate.edu/research/irb/irb_inquiry.html

==

Institutional Review Board

Office of Research Compliance

Texas State University-San Marcos

(ph) 512/245-2314 / (fax) 512/245-3847 / ospirb@txstate.edu / JCK 489

601 University Drive, San Marcos, TX 78666

7. Survey Questionnaire

1. Paper Survey

Question 1 of 14

What is your birth year? Please give your answer using four digits for the year.

Y Y Y Y

Question 2 of 14

What is your sex? Please check one.

- ◯ Female
- ◯ Male

Question 3 of 14

How would you identify yourself? Please check all that apply

- ◯ White or Caucasian
- ◯ Black or African-American
- ◯ Asian
- ◯ Hispanic, Latino, or Spanish
- ◯ Native American
- ◯ Other is

Question 4 of 14

Were you born in the United States? Please check one.

- ◯ Yes
- ◯ No

Question 5 of 14

About how many hours a week do you spend in the following academic activities?

- ☐ Teaching (hours a week)
- ☐ Research (hours a week)
- ☐ Administration (hours a week)
- ☐ Other academic activities (hours a

Main “other” activities are:

Question 6 of 14

What is your subdiscipline? Enter percentage of time spent in each.

- [ ] GIScience (% of time)
- [ ] Human geography (% of time)
- [ ] Physical geography (% of time)
- [ ] Regional geography (% of time)
- [ ] Other (% of time)

What subdisciplines does “Other” include :

Question 7 of 14

Have you been awarded tenure? Please check "yes" or "no."

- ◯ Yes → **If "Yes" enter year tenure awarded** ______ (YYYY) → **Go to Question 8**
- ◯ No

Is your current academic appointment on a tenure track? Please check "yes" or "no." If "yes" enter year using four digits.

- ◯ Yes → **If "Yes" enter year first started on tenure track** ______ (YYYY)
- ◯ No

Question 8 of 14

Have you been awarded contracts or external grant funding? Please check "yes" or "no."

- ◯ Yes
- ◯ No → **If "No" go to Question 9**

Enter amount ($) and number of years. Include ~ last 10 years.

Grant Funding: $ ______ over ______ years

Contracts: $ ______ over ______ years

NOTE: If more convenient you can attach your CV to an e-mail and send it to me at JP1647@txstate.edu

Question 9 of 14

What best describes your marital status? Please check one.

- ○ Legal **marriage**
- ○ Committed **relationship** for > 1 year

If legal marriage or committed relationship go to Question 10

- ○ **Single** (includes widowed, separated, or divorced)
- ○ **Never married**

If single or never married go to Question 12

Question 10 of 14

Is your spouse or partner employed full-time? Please check best option.

- ○ My spouse or partner works **full-time**
- ○ My spouse or partner works **part-time** - about ____ hours/week
- ○ My spouse or partner **does not work**

Question 11 of 14

Does your spouse or partner work at any of the following? Check all that apply.

- ◯ My spouse or partner works at **a college or university**
- ◯ My spouse or partner works at **my college or university**
- ◯ My spouse or partner works in **my department**
- ◯ None of the above

Question 12 of 14

Enter the birth years of the children living with you.
Please give your answer using four digits for the year.

◯ **No children**

Birth year 1st Child:	YYYY	Birth year 4th Child:	YYYY
Birth year 2nd Child:	YYYY	Birth year 5th Child:	YYYY
Birth year 3rd Child:	YYYY	Birth year 6th Child:	YYYY

If more >6 children e-mail list to JP1647@txstate.edu

Are you the primary caregiver for someone other than these children?

- ◯ **Yes**
- ◯ **No**

Question 13 of 14

How much was your job search limited geographically. Please check the better option.

◯ There was **no geographic limitation** in my job

◯ My job search **was limited** to these institutions, cities, or states:

Reasons for limitations:

Question 14 of 14

In presidential elections which party do you usually vote for or would you vote for? Please check the best option.

◯ Republican Party

◯ Democratic Party

◯ No opinion

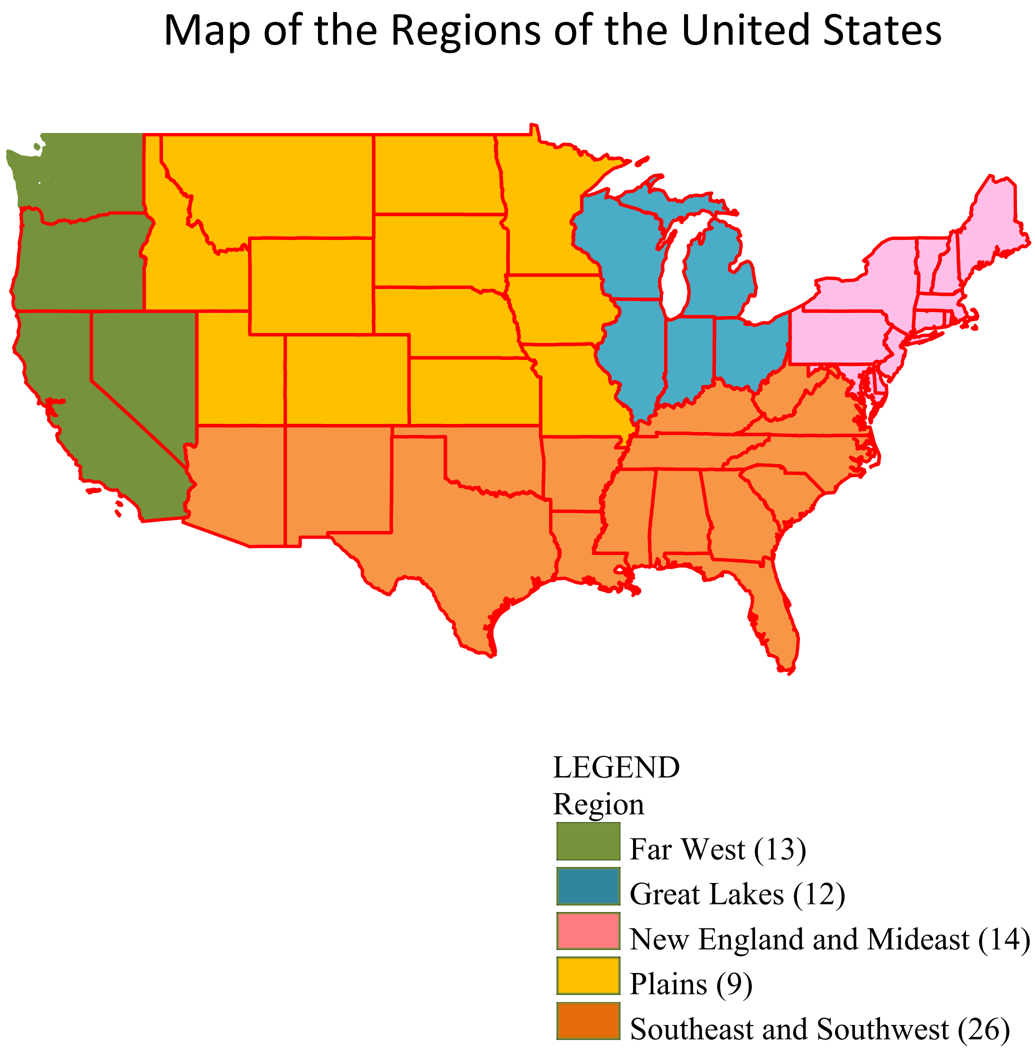

Figure 1. Map of geographic regions of the United States. Total number of institutions for each region are shown in parenthesis; the overall total number of institutions is 74. Alaska and Hawaii are in the Far West, but are not shown.

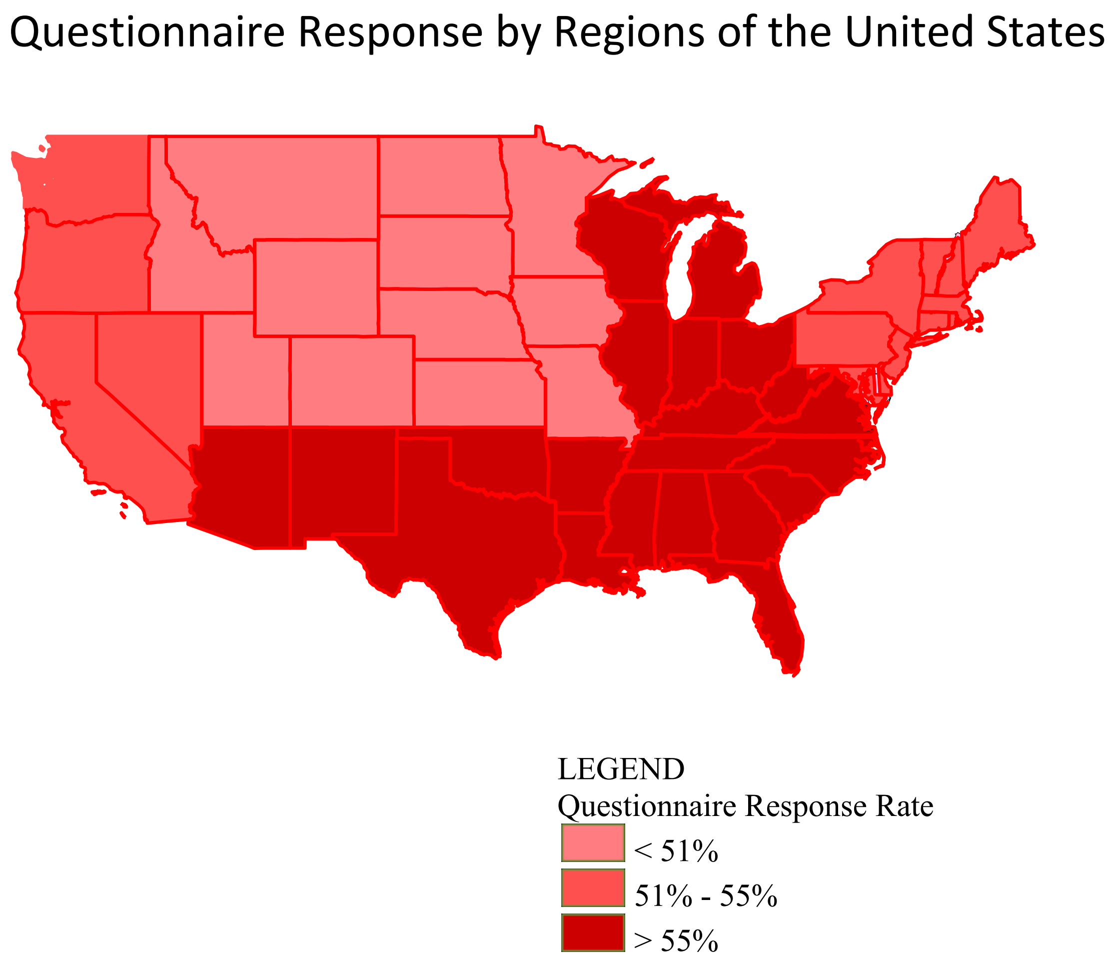

Figure 2. Map of questionnaire response by regions of the United States. Overall questionnaire response rate was 53%.

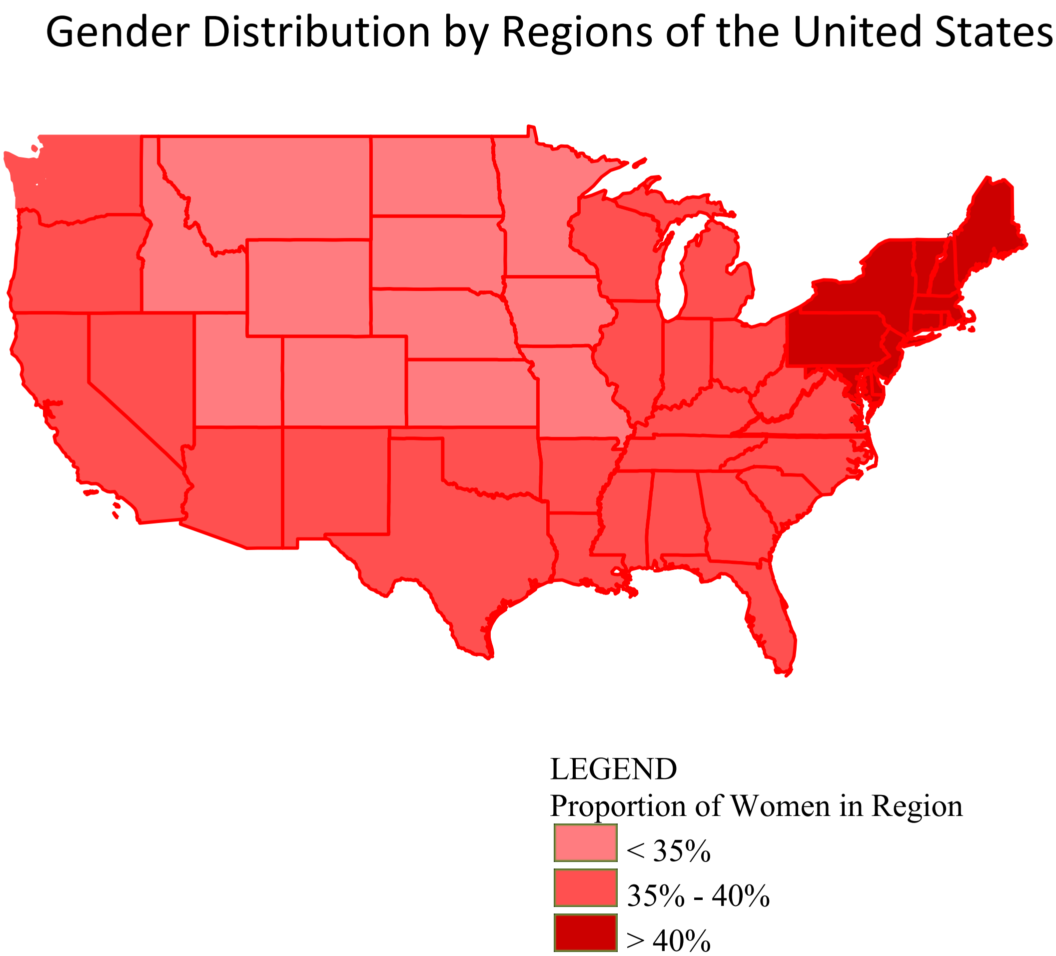

Figure 3. Map of gender distribution by regions of the United States. Overall females were 39% of the total.

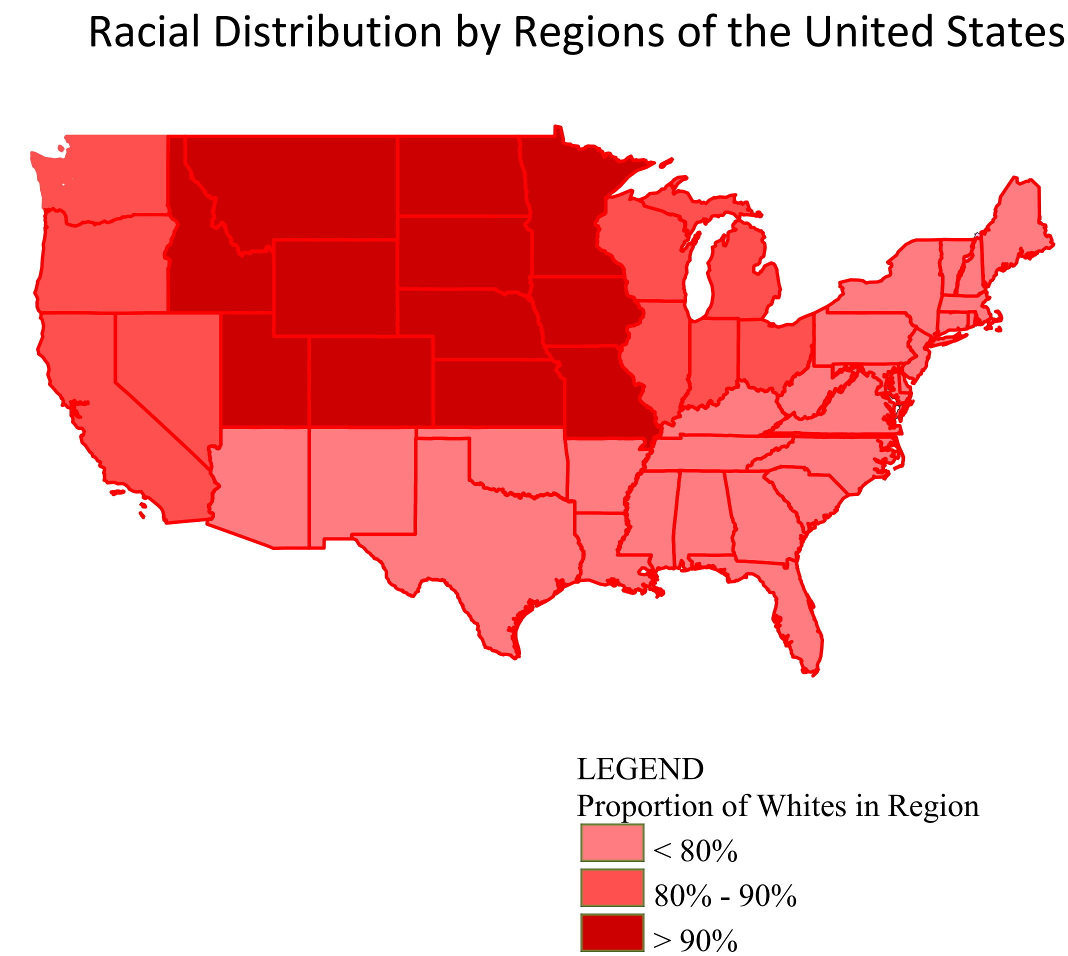

Figure 4. Map of racial distribution by regions of the United States. Overall whites were 82% of the population.

Table 2. Published Data on Promotion Variables.

Variable/Field	Paper	Gender Difference	Regression Promotion Effect
Age			
All Fields	Astin and Bayer (1972)	Not reported	Positive men and women
All Fields	Bayer (1973)	No difference	Not reported
All Fields	Bayer and Astin (1975)	Not reported	Positive men and women
Economics	Ginther and Kahn (2004)	No difference	Positive men and women
Humanities	Ginther and Hayes (2003)	No difference	Positive men and women
Science	Ginther and Kahn (2006)	Women older than men	Positive men and women
Gender			
All Fields	Astin and Bayer (1972)	Not reported	Negative for women
All Fields	Bayer (1973)	Full professor: women 19% less than men	Not reported
All Fields	Bayer and Astin (1975)	Not reported	Negative for women
All Fields	Nettles et al. (2000)	Full professor: women 24% less than men	Not reported
All Fields	Perna (2001)	Full professor: women 25% less than men	Not reported
All Fields	Raymond et al. (1993)	Full professor: women 29% less than men	Women 13% less than men
Arts and Sciences	Roos and Gatta (2009)	No difference	Not reported
Biochemistry	Long et al. (1993)	Not reported	Women 10% less than men
Economics	Ginther and Kahn (2004)	Not reported	Women 21% less than men
Engineering and Science	Kaminski and Geisler (2012)	No difference	Not reported
Geography	Zelinsky (1973)	Full professor: women 16% less than men	Not reported
Humanities	Ginther and Hayes (2003)	Full professor: women 15% less than men	Women 8% less than men
Life Science	Ginther and Kahn (2004)	No difference	Not reported
Physical Science	Ginther and Kahn (2004)	No difference	Not reported
Political Science	Ginther and Kahn (2004)	No difference	Not reported
Political Science	Hesli et al. (2012)	Full professor: women 16% less than men	Women 49% less than men
Science	Bayer and Astin (1968)	No difference	Not reported
Science	Ginther and Kahn (2006)	No difference	Not reported
Science	Ginther (2001)	Full professor: women 24% less than men	Negative only for women
Social Science	Ginther and Kahn (2004)	Tenure: women 8.1% less than men	Not reported
Statistics	Ginther and Kahn (2004)	No difference	Not reported

Table 2. Published Data on Promotion Variables (continued).

Variable/Field	Paper	Gender Difference	Regression Promotion Effect
RACE			
White			
All Fields	Bayer (1973)	More white men than women	Positive only for men
All Fields	Bayer and Astin (1975)	Positive for men and women	Not reported
All Fields	Nettles et al. (2000)	More white men than women	No difference
Black			
All Fields	Bayer (1973)	More black women than men	Not reported
All Fields	Nettles et al. (2000)	No difference	Varies with rank
Economics	Ginther and Kahn (2004)	No difference	Negative
Humanities	Ginther and Hayes (2003)	More black women than men	Negative
Science	Gintner and Kahn (2006)	More black women than men	No difference
Asian			
All Fields	Bayer (1973)	No difference	Not reported
All Fields	Nettles et al. (2000)	More Asian men than women	Not reported
PhD Top Program			
All Fields	Astin and Bayer (1972)	Not reported	Positive for men and women
Biochemistry	Long et al. (1993)	No difference	No effect
Economics	Ginther and Kahn (2004)	Women more than men by 6%	Negative for men and women
Humanities	Ginther and Hayes (2003)	Women less than men by 2%	Positive for men and women
Science	Ginther and Kahn (2006)	Women less than men by 3%	No effect
Years from PhD to Hiring as Assistant Professor			
Biochemistry	Long et al. (1993)	Women take longer than men	Negative only for women
Humanities	Ginther and Hayes (2003)	No difference	Negative for men and women

Table 2. Published Data on Promotion Variables (continued).

Variable/Field	Paper	Gender Difference	Regression Promotion Effect
Inbred			
All Fields	McGee (1960)	Negative for men and women	Not reported
Biochemistry	Long et al. (1993)	No difference	No effect
Sciences	Hargens and Farr (1973)	Negative for men and women	Not reported
Work Top Program			
Biochemistry	Long et al. (1993)	No difference	Negative for men and women
Economics	Ginther and Kahn (2004)	Women more than men by 5%	Varies with regression model
Humanities	Ginther and Hayes (2003)	No difference	Positive for men and women
Science	Ginther and Kahn (2006)	Women less than men by 3%	Varies field
TIME ALLOCATION			
Teaching			
All Fields	Bayer (1973)	Women more than men	Not reported
All Fields	Nettles et al. (2000)	Women more than men	Not reported
All Fields	Winslow (2010)	Women more than men	Not reported
Economics	Manchester et al. (2013)	Women more than men	Not reported
STEM	Xie and Shauman (1998)	Women more than men	Not reported
Research			
All Fields	Bayer (1973)	Men more than women	Not reported
All Fields	Nettles et al. (2000)	Men more than women	Not reported
All Fields	Winslow (2010)	Men more than women	Not reported
Economics	Manchester et al. (2013)	Men more than women	Not reported
Administrative			
All Fields	Astin and Bayer (1972)	Not reported	Positive for men and women
All Fields	Bayer (1973)	Men more than women	Not reported
All Fields	Nettles et al. (2000)	No difference	Not reported

Table 2. Published Data on Promotion Variables (continued).

Variable/Field	Paper	Gender Difference	Regression Promotion Effect
Total Hours Worked			
All Fields	Jacobs et al. (2004)	Men 2 hours/week more	Not reported
STEM	Ceci et al. (2014)	Women more or no difference	Not reported
Time to Promotion			
Biochemistry	Long et al. (1993)	Women 0.2 yrs slower	Not reported
Engineering	Kaminski and Geisler (2012)	No difference	Not reported
Humanities	Ginther and Hayes (2003)	Women 0.42 years slower	Not reported
Science	Ginther (2001)	Women 0.68 years faster	Not reported
Science	Ginther and Kahn (2006)	No difference time to tenure	Not reported
Papers Before Hired			
Biochemistry	Long et al. (1993)	Women more than men	No effect
Papers Published			
All Fields	Astin and Bayer (1972)	Not reported	Positive for men and women
All Fields	Bayer (1973)	Men more papers than women	Not reported
All Fields	Ferber et al. (1982)	Varies with field	Not reported
All Fields	Nettles et al. (2000)	Men more papers than women	Not reported
All Fields	Sax et al. (2002)	Men more papers than women	Not reported
Biochemistry	Long et al. (1993)	Men more papers than women	Positive for men and women
Criminology	Snell et al. (2009)	No difference	Positive for women
Economics	Ginther et al. (2004)	No difference	Positive for men and women
Humanities	Ginther et al. (2003)	No difference	Positive for men and women

Table 2. Published Data on Promotion Variables (continued).

Variable/Field	Paper	Gender Difference	Regression Promotion Effect
Papers Published			
Political Science	Hesli et al. (2012)	Men publish more papers than women	Positive men and women
Psychology	Astin (1972)	Men publish more papers than women	Not reported
Science	Fox (2005)	Men publish more papers than women	Not reported
Science	Ginther et al. (2006)	Men publish more papers than women	Positive most fields
Science	Levin et al. (1998)	Men publish more papers than women	Not reported
Social Work	Fox et al. (1985)	Men publish more papers than women	Not reported
STEM	Ceci et al. (2014)	Men publish more papers than women	Not reported
STEM	Cole et al. (1984)	Men publish more papers than women	Not reported
STEM	Xie et al. (1998)	Men publish more papers than women	Not reported
Citations Before Hired			
Biochemistry	Long et al. (1993)	No difference	No effect
Citations			
Biochemistry	Long et al. (1993)	No difference	No effect
Economics	Ginther et al. (2004)	No difference	Not reported
Grant Funding			
All Fields	Bayer (1973)	More men funded than women	Not reported
All Fields	Ferber et al. (1982)	Men more funds than women	Not reported
All Fields	Nettles et al. (2000)	More men funded than women	Not reported
Moves			
Biochemistry	Long et al. (1993)	No difference	Negative for men and women
Criminology	McElrath (1992)	Men move more than women	Negative only for women
Psychology	Rosenfeld et al. (1987)	Men move more than men	Negative for men and women
Science	Ginther and Kahn (2006)	Women move more than men	Negative for men and women

Table 2. Published Data on Promotion Variables (continued).

Variable/Field	Paper	Gender Difference	Regression Promotion Effect
Married			
All Fields	Bayer (1973)	More men married than women	Not reported
All Fields	Mason and Goulden (2004)	More men married than women	Not reported
All Fields	Astin and Milem (1997)	More men married than women	Not reported
Art History	Rudd et al. (2008)	No difference	Positive only for men
Biochemistry	Long et al. (1993)	More men married than women	Positive for men and women
Humanities	Ginther and Hayes (2003)	More men married than women	No effect
Political Science	Hesli et al. (2012)	More men married than women	No effect
Science	Ginther (2001)	More men married than women	Positive for men and women
Science	Goulden et al. (2011)	More men married than women	Not reported
Social Work	Fox and Faver (1985)	More men married than women	Not reported
Spouse Works			
All Fields	Bayer (1973)	More women than men	Not reported
All Fields	Jacobs and Winslow (2004)	More women than men	Not reported
Spouse Works Full-Time			
All Fields	Jacobs and Winslow (2004)	More women than men	Not reported
Art History	Rudd et al. (2008)	More women than men	Not reported
Geoscience	Macfarlane et al. (1998)	More women than men	Not reported
Spouse Works University			
All Fields	Bayer (1973)	No difference	Not reported
All Fields	Jacobs and Winslow (2004)	More women than men	Not reported
All Fields	Astin and Milem (1997)	More women than men	Positive for men and women
Spouse Works Same Institution			
All Fields	Perna (2005)	No difference	Not reported

Table 2. Published Data on Promotion Variables (continued).

Variable/Field	Paper	Gender Difference	Regression Promotion Effect
Children			
All Fields	Astin and Bayer (1972)	Not reported	Positive for men and women
All Fields	Bayer (1973)	Men more children than women	Not reported
All Fields	Jacobs and Winslow (2004)	Men more children than women	Not reported
All Fields	Mason and Goulden (2004)	Men more children than women	Not reported
All Fields	Perna (2005)	Men more children than women	Not reported
Biochemistry	Long et al. (1993)	Men more children than women	No effect
Chemistry	Hargens et al. (1978)	No difference	Not reported
Economics	Ginther and Kahn (2004)	No difference	Negative only for women
Humanities	Ginther and Hayes (2003)	Men more children than women	Positive effect for men and women
Science	Ginther and Kahn (2006)	Men more children than women	Positive effect for men and women
Science	Goulden et al. (2011)	Men more children than women	Not reported
Children			
Social Work	Fox and Faver (1985)	Men more children than women	Not reported
STEM	Stack (2004)	Men more children than women	Not reported
STEM	Sax et al. (2002)	Men more children than women	No effect
Early Baby			
Sciences	Mason and Goulden (2002)	More early babies for men than women	Positive only for men
Young Children			
Biochemistry	Long et al. (1993)	More young children for men than women	No effect
Economics	Ginther and Kahn (2004)	More young children for men than women	Positive for men and women
Science	Ginther and Kahn (2006)	More young children for men than women	No effect
Social Science	Morrison et al. (2011)	More young children for men than women	No effect
Social Work	Fox and Faver (1985)	More young children for men than women	Not reported

Table 2. Published Data on Promotion Variables (continued).

Variable/Field	Paper	Gender Difference	Regression Promotion Effect
Job Search			
All Fields	Bayer (1973)	Women more concerned than men	Not reported
All Fields	Kulis and Sicotte (2002)	Women more limited than men	Negative for men and women
All Fields	Marwell et al. (1979)	Women more limited than men	Not reported
Psychology	Rosenfeld and Jones (1987)	Women move less than men	Not reported
Political Vote			
All Fields	Astin and Bayer (1972)	Not reported	Negative for men and women
All Fields	Bayer (1973)	Women more conservative than men	Not reported
All Fields	Cardiff and Klein (2005)	Women favor Democrats than men do	Not reported
All Fields	Zipp and Fenwick (2006)	Women more liberal politically than men	Not reported

Table 3. Research Designs Used in Studies Evaluating Academic Promotion.

Cross-Sectional – Descriptive Analysis

Field	Paper	Period	Region	Rank	Promotion Result
All	Alpert (1989)	1987	National	Professor	Women ↓35%
All	Astin et al. (1972)	1969	National	Tenure	Women ↓11%
All	Astin et al. (1972)	1969	National	Professor	Women ↓16%
All	Nettles (2000)	1993	National	Tenure	Women ↓24%
All	Nettles (2000)	1993	National	Professor	Women ↓24%
All	Perna (2001)	1993	National	Tenure	Women ↓19%
All	Perna (2001)	1993	National	Professor	Women ↓25%
All	Szafran (1983)	1969	National	Tenure	Women ↑5%
All	Szafran (1983)	1969	National	Rank	Women ↓11%
All	Toutkoushian (1998)	1993	National	Associate	Women ↑2%
All	Toutkoushian (1998)	1993	National	Professor	Women ↓25%
Arts/Science	Roos et al. (2009)	2003-2004	State U	Associate	Women ↓12%
Arts/Science	Roos et al. (2009)	1999-2004	State U	Professor	Women ↓10%
Biochemistry	Long et al. (1993)	1956-1967	National	Associate	Women ↓10%
Biochemistry	Long et al. (1993)	1956-1967	National	Professor	Women ↓20%
Economics	Ginther et al. (2004)	1973-2001	National	Tenure	Women ↓21%
Economics	Ginther et al. (2004)	1980-2001	National	Tenure	Women ↓11%
Geography	Zelinski (1973)	1876-1949	National	Associate	Women ↓4%
Geography	Zelinski (1973)	1876-1949	National	Professor	Women ↓16%
Geography	Luzzadder-Beach et al. (2000)	1995-1996	National	Associate	Women ↓8%
Geography	Luzzadder-Beach et al (2000)	1995-1996	National	Professor	Women ↓19%
Geoscience	Macfarlane et al. (1998)	1994-1996	National	Associate	Women ↓7%
Geoscience	Macfarlane et al. (1998)	1994-1996	National	Professor	Women ↓16%
Humanities	Ginther et al. (2003)	1977-1995	National	Associate	Women ↑4%
Humanities	Ginther et al. (2003)	1977-1995	National	Professor	Women ↓15%
Science	Ginther (2001)	1973-1997	National	Associate	Women ↓6%
Science	Ginther (2001)	1973-1997	National	Professor	Women ↓24%
Science and Engineering	CEEWISE (1979)	1977	National	Associate	Women ↓10%
Science and Engineering	CEEWISE (1979)	1977	National	Professor	Women ↓4%
Science and Engineering	Long (2001)	1979	National	Associate	Women ↓2%

Table 3. Research Designs Used in Studies Evaluating Academic Promotion (continued).

Cross-Sectional – Descriptive Analysis (continued)

Field	Paper	Period	Region	Rank	Promotion Result
Science and Engineering	Long (2001)	1989	National	Associate	Women ↓8%
Science and Engineering	Long (2001)	1995	National	Associate	Women ↓7%
Science and Engineering	Long (2001)	1979	National	Professor	Women ↓27%
Science and Engineering	Long (2001)	1989	National	Professor	Women ↓28%
Science and Engineering	Long (2001)	1995	National	Professor	Women ↓27%

Cross-Sectional – Regression Analysis

Field	Paper	Period	Region	Rank	Promotion Result
All	Perna (2001)	1993	National	Tenure	Women ↓3%
Humanities	Ginther et al. (2003)	1977-1995	National	Tenure	Women ↓8%
Political Science	Hesli et al. (2012)	2009	National	Associate	Women ↓51%

Longitudinal Cohort – Linear Regression

Field	Paper	Period	Region	Rank	Promotion Result
Economics	Ginther et al. (2004)	1980-2001	US/Canada	Tenure	Women ↓15%
Economics	Ginther et al. (2004)	1972-2001	National	Tenure	Women ↓13%
Humanities	Ginther et al. (2003)	1977-1995	National	Associate	Women ↓8%
Humanities	Ginther et al. (2003)	1975-1979	National	Associate	Women ↓9%
Humanities	Ginther et al. (2003)	1980-1990	National	Associate	Women ↓7%
Science	Ginther (2001)	1973-1997	National	Associate	Women ↓7%
Science	Ginther (2001)	1972-1979	National	Associate	Women ↓7%
Science	Ginther (2001)	1980-1989	National	Associate	Women ↓8%

Table 3. Research Designs Used in Studies Evaluating Academic Promotion (continued).

Longitudinal Cohort – Logistic Regression

Field	Paper	Period	Region	Rank	Promotion Result
Biochemistry	Long et al. (1993)	1956-1967	National	Associate	Women ↓10%
Biochemistry	Long et al. (1993)	1956-1967	National	Professor	Women ↓20%
Humanities	Ginther et al. (2003)	1977-1995	National	Associate	Women ↓8%
Humanities	Ginther et al. (2003)	1975-1979	National	Associate	Women ↓7%
Humanities	Ginther et al. (2003)	1980-1989	National	Associate	Women ↓6%
Science	Ginther (2001)	1973-1997	National	Associate	Women ↓7%
Science	Ginther (2001)	1972-1979	National	Associate	Women ↓7%
Science	Ginther (2001)	1980-1989	National	Associate	Women ↓8%
Science and Engineering	Long (2001)	1979	National	Tenure	Women ↓17%
Science and Engineering	Long (2001)	1989	National	Tenure	Women ↓6%
Science and Engineering	Long (2001)	1995	National	Tenure	Women ↓4%
Science and Engineering	Long (2001)	1979	National	Professor	Women ↓20%
Science and Engineering	Long (2001)	1989	National	Professor	Women ↓12%
Science and Engineering	Long (2001)	1995	National	Professor	Women ↓9%

Table 3. Research Designs Used in Studies Evaluating Academic Promotion (continued).

Longitudinal Cohort – Survival Curves

Field	Paper	Period	Region	Rank	Promotion Result
Economics	Ginther et al. (2004)	1972-2001	National	Tenure	Women ↓21%
Engineering	Ginther et al. (2004)	1972-2001	National	Tenure	Women ↑
Engineering	Ginther et al. (2006)	1973-2001	National	Tenure	No difference
Life Science	Ginther et al. (2004)	1972-2001	National	Tenure	No difference
Life Science	Ginther et al. (2006)	1973-2001	National	Tenure	No difference
Physical Science	Ginther et al. (2004)	1972-2001	National	Tenure	No difference
Physical Science	Ginther et al. (2006)	1973-2001	National	Tenure	No difference
Political Science	Ginther et al. (2004)	1972-2001	National	Tenure	No difference
Science	Ginther et al. (2006)	1973-2001	National	Tenure	No difference
Science and Engineering	Kaminski et al. (2012)	1990-2009	National	Exit	No difference
Statistics	Ginther et al. (2004)	1972-2001	National	Tenure	No difference

Longitudinal Cohort – Cox Regression

Field	Paper	Period	Region	Rank	Promotion Result
Economics	Ginther et al. (2004)	1972-2001	National	Tenure	Not reported
Humanities	Ginther et al. (2003)	1977-1995	National	Associate	0.795
Humanities	Ginther et al. (2003)	1975-1979	National	Associate	0.778
Humanities	Ginther et al. (2003)	1980-1989	National	Associate	0.824
Science	Ginther (2001)	1973-1997	National	Associate	0.879
Science	Ginther (2001)	1972-1979	National	Associate	0.868
Science	Ginther (2001)	1980-1989	National	Associate	0.940

Table 3. Research Designs Used in Studies Evaluating Academic Promotion (continued).

Longitudinal Matched Cohorts

Field	Paper	Period	Region	Rank	Promotion Result
Psychology	Marwell et al. (1979)	1955-1970	National	Mobility	Women ↓1/2
Zoology	Bernard (1966)	Not given	State	Papers	No difference
All	Ahern et al. (1981)	1940s-1950s	National	Tenure	Women ↓9%
All	Ahern et al. (1981)	1940s-1950s	National	Professor	Women ↓23%
All	Ahern et al. (1981)	1960s	National	Associate	Women ↑2%
All	Ahern et al. (1981)	1960s	National	Tenure	Women ↓8%
All	Ahern et al. (1981)	1960s	National	Professor	Women ↓19%
All	Ahern et al. (1981)	1970-1974	National	Associate	Women ↓13%
All	Ahern et al. (1981)	1970-1974	National	Tenure	Women ↓17%
All	Ahern et al. (1981)	1970-1974	National	Professor	Women ↓3%
All	Ahern et al. (1981)	1975-1978	National	Associate	Women ↓5%
All	Ahern et al. (1981)	1975-1978	National	Tenure	Women ↓6%

Table 4. Academic Promotion Studies Not Based on Survey of Doctorate Recipients.

Cross-Sectional – Descriptive Analysis

Field	Paper	Period	Region	Rank	Promotion Result
All	Astin et al. (1972)	1969	National	Tenure	Women ↓11%
All	Astin et al. (1972)	1969	National	Professor	Women ↓16%
All	Nettles (2000)	1993	National	Tenure	Women ↓24%
All	Nettles (2000)	1993	National	Professor	Women ↓24%
All	Perna (2001)	1993	National	Tenure	Women ↓19%
All	Perna (2001)	1993	National	Professor	Women ↓25%
All	Szafran (1983)	1969	National	Tenure	Women ↓11%
All	Szafran (1983)	1969	National	Rank	Women ↑5%
All	Toutkoushian (1998)	1993	National	Associate	Women ↑2%
All	Toutkoushian (1998)	1993	National	Professor	Women ↓25%
Arts and Science	Roos et al. (2009)	2003-2004	State U	Associate	Women ↓12%
Arts and Science	Roos et al. (2009)	1999-2004	State U	Professor	Women ↓10%
Biochemistry	Long et al. (1993)	1956-1967	National	Associate	Women ↓16%
Biochemistry	Long et al. (1993)	1956-1967	National	Professor	Women ↓20%
Geography	Zelinski (1973)	1876-1949	National	Associate	Women ↓4%
Geography	Zelinski (1973)	1876-1949	National	Professor	Women ↓16%
Geography	Luzzadder-Beach et al. (2000)	1995-1996	National	Associate	Women ↓8%
Geography	Luzzadder-Beach et al. (2000)	1995-1996	National	Professor	Women ↓19%
Geoscience	Macfarlane et al. (1998)	1994-1996	National	Associate	Women ↓7%
Geoscience	Macfarlane et al. (1998)	1994-1996	National	Professor	Women ↓16%

Table 4. Academic Promotion Studies Not Based on Survey of Doctorate Recipients (continued).

Cross-Sectional – Regression Analysis

Field	Paper	Period	Region	Rank	Promotion Result
All	Perna (2001)	1993	National	Tenure	Women ↓3%
Political Science	Hesli et al. (2012)	2009	National	Associate	Women ↓51%

Longitudinal Cohort – Logistic Regression

Field	Paper	Period	Region	Rank	Promotion Result
Biochemistry	Long et al. (1993)	1956-1967	National	Associate	Women ↓10%
Biochemistry	Long et al. (1993)	1956-1967	National	Professor	Women ↓20%

Longitudinal Cohort – Survival Curves

Field	Paper	Period	Region	Rank	Promotion Result
Science and Engineering	Kaminski et al. (2012)	1990-2009	National	Exit	No difference

Longitudinal – Matched Cohorts

Field	Paper	Period	Region	Measured	Result
Zoology	Bernard (1966)	1947-1948	State	Papers	No difference

Table 9. Variables Reported to Predict Promotion with Significant p-Values

Papers Published

Field	Paper	Promotion Effect	p-Value
All Fields	Astin and Bayer (1972)	Positive	$p < 0.0001$
Biochemistry	Long et al. (1993)	Positive	$p < 0.001$
Criminology	McElrath (1992)	Positive for men	$p < 0.05$
Economics	Ginther and Kahn (2004)	Positive	$p < 0.01$
Humanities	Ginther and Hayes (2003)	Positive	$p < 0.05$
Political Science	Hesli et al (2012)	Positive	$p < 0.01$
Science	Ginther and Kahn (2006)	Positive most fields	$p < 0.01$

Gender

Field	Paper	Promotion Effect	p-Value
All Fields	Bayer and Astin (1975)	Negative women	$p < 0.001$
All Fields	Raymond et al. (1993)	Negative women	$p < 0.05$
Biochemistry	Long et al. (1993)	Negative women	Not significant
Humanities	Ginther and Hayes (2003)	Negative women	$p < 0.01$
Economics	Ginther and Kahn (2004)	Negative women	$p < 0.01$
Science	Ginther (2001)	Negative women	$p < 0.01$

Work Top Program

Field	Paper	Promotion Effect	p-Value
Biochemistry	Long et al (1993)	Negative	$p < 0.01$
Economics	Ginther and Kahn (2004)	Positive women	$p < 0.01$
Science	Ginther and Kahn (2006)	Varies field	$p < 0.05$ at best

Years PhD to Hired

Field	Paper	Promotion Effect	p-Value
Biochemistry	Long et al (1993)	Negative	$p < 0.05$
Humanities	Ginther and Hayes (2003)	Negative	$p < 0.01$

Table 9. Variables Reported to Predict Promotion with Significant p-Values (continued)

PhD Top Program

Field	Paper	Promotion Effect	p-Value
All Fields	Astin and Bayer (1972)	Positive men	$p < 0.01$
Biochemistry	Long et al (1993)	No effect	Not significant
Economics	Ginther and Kahn (2004)	Negative	$p < 0.05$
Science	Ginther and Kahn (2006)	Usually no effect	$p < 0.05$ at best

Moves

Field	Paper	Promotion Effect	p-Value
Biochemistry	Long et al. (1993)	Negative	$p < 001$
Criminology	McElrath (1992)	Negative for women	$p < 0.05$
Science	Ginther and Kahn (2006)	Negative	$p < 0.01$

Married

Field	Paper	Promotion Effect	p-Value
All Fields	Astin and Bayer (1972)	Positive (single)	$p < 0.001$
Biochemistry	Long et al (1993)	Positive	$p < 0.01$
Humanities	Ginther and Hayes (2003)	No effect	Not significant
Political Science	Hesli et al (2012)	No effect	Not significant
Science	Ginther (2001)	Positive	$p < 0.01$ at best

Children

Variable	Paper	Promotion Effect	p-Value
All Fields	Astin and Bayer (1972)	Positive	$p < 0.001$
All Fields	Perna (2005)	Positive men	$p < 0.05$
Biochemistry	Long et al (1993)	No effect	Not significant
Humanities	Ginther and Hayes (2003)	Positive	$p < 0.05$
Science	Ginther and Kahn (2006)	Positive	$p < 0.001$

Table 9. Variables Reported to Predict Promotion with Significant p-Values (continued)

Midwest Region

Variable	Paper	Promotion Effect	p-Value
All Fields	Bayer and Astin (1975)	Positive	$p < 0.001$

Time in Administration

Field	Paper	Promotion Effect	p-Value
All Fields	Astin and Bayer (1972)	Positive	$p < 0.001$

Spouse Works University

Field	Paper	Promotion Effect	p-Value
All Fields	Astin and Milem (1997)	Positive	$p < 0.001$

Foreign Born

Field	Paper	Promotion Effect	p-Value
All Fields	Astin and Bayer (1972)	Positive	$p < 0.01$

Political Vote

Field	Paper	Promotion Effect	p-Value
All Fields	Astin and Bayer (1972)	Negative	$p < 0.01$

Young Children

Field	Paper	Promotion Effect	p-Value
Biochemistry	Long et al (1993)	No effect	Not significant
Economics	Ginther and Kahn (2004)	Positive	$p < 0.05$
Science	Ginther and Kahn (2006)	No effect	Not significant

Table 9. Variables Reported to Predict Promotion with Significant p-Values (continued)

Race: Black

Field	Paper	Promotion Effect	p-Value
Economics	Ginther and Kahn (2004)	Negative	$p < 0.05$
Humanities	Ginther and Hayes (2003)	Negative	$p < 0.05$
Science	Gintner and Kahn (2006)	Negative	Not significant

Citations Before Hired

Field	Paper	Promotion Effect	p-Value
Biochemistry	Long et sl (1993)	No effect	Not significant

Citations

Field	Paper	Promotion Effect	p-Value
Biochemistry	Long et al (1993)	No effect	Not significant

Inbred

Field	Paper	Promotion Effect	p-Value
Biochemistry	Long et al (1993)	No effect	Not significant

Papers Before Hired

Field	Paper	Promotion Effect	p-Value
Biochemistry	Long et al (1993)	No effect	Not significant

Table 12. Comparison of Variable Values According to Questionnaire Response.

Interval Variables

	Questionnaire Response Present	Absent
Year of PhD	1992.6 (463)	1992.9 (406)
PhDHire	4.19 (463)	3.62 (406)
Top PhD	33.4% (463)	32.8% (406)
Publications:		
When Hired	1.68 (463)	1.63 (406)
Before AscP	13.2 (392)	13.3 (457)
Before Prof	26.5 (241)	26.9 (260)
Citations:		
When Hired	44.7 (463)	46.4 (406)
Before AscP	281.2 (392)	342.4 (457)
Before Prof	545.2 (241)	692.3 (260)
AssP Moves:		
Number	0.270 (463)	0.246 (406)
To PhD-granting	0.259 (463)	0.291 (406)

Professor's Research Focus

	Questionnaire Response Present	Absent	|Difference|
Geography	62.0% (287)*	56.9% (231)	5.1%
Geology	5.4% (25)	9.4% (38)	4.0%
Ecology	6.3% (29)	5.9% (24)	0.4%
Urban Planning	5.2% (24)	4.9% (20)	0.3%
Anthropology	3.9% (18)	4.9% (20)	1.0%
Metrology	5.2% (24)	4.2% (17)	1.0%
Engineering	4.3% (20)	3.7% (15)	0.6%
Sociology	2.8% (13)	3.7% (15)	0.9%
Economics	2.4% (11)	3.2% (13)	0.8%
Policy	1.7% (8)	1.2% (5)	0.5%
History	0.6% (3)	1.2% (5)	0.6%
Education	0.2% (1)	0.8% (3)	0.6%
TOTAL	100% (463)	100% (406)	

Table 12. Comparison of Variable Values According to Questionnaire Response (continued).

Region

	Questionnaire Response	
	Present	Absent
South	33.9%	30.0%
West	18.4%	21.7%
New Eng	22.0%	23.2%
Lakes	16.2%	14.5%
Plains	9.5%	10.6%
Total	100%	100%

Number of professors is shown in parenthesis.
|Difference| is the absolute value of the difference.

Table 14. List of PhD-Granting Institutions with the Gender Ratio for Each.

	Male		Female			
	N	Mean Year of PhD	N	Mean Year of PhD	Difference Year of PhD	Ratio M/F
ARIZONA (AZ)						
AZ State U	14	1991	8	1993	1.39	1.75
U AZ-Tucson	13	1991	9	1992	1.29	1.44
CALIFORNIA (CA)						
San Diego State U	13	1993	7	1998	4.64	1.86
U CA-Berkeley	9	1989	5	1988	-1.29	1.80
U CA-Davis	25	1990	16	1990	0.00	1.63
U CA-Los Angeles	8	1992	4	1992	0.25	2.00
U CA-Riverside	4	1986	2	1988	2.00	2.00
U CA-Santa Barbara	9	1993	4	1995	2.25	2.25
U Southern CA	6	1983	3	1988	5.17	2.00
COLORADO (CO)						
U CO-Boulder	10	1994	5	1995	0.60	2.00
CONNECTICUT (CT)						
U CO-Storrs	4	1996	4	1999	3.25	1.00
DELAWARE (DE)						
U DE-Newark	3	1992	3	1986	-5.33	1.00
FLORIDA (FL)						
FL Atlantic U	8	1996	3	1995	-0.67	2.67
FL International U	8	1983	9	1996	12.94	0.89
FL State U	5	1996	2	2001	4.80	2.50
U FL-Gainesville	3	1991	3	1993	2.00	1.00
U Miami	2	1994	1	2005	11.50	2.00
U South FL	7	1998	8	2001	3.14	0.88
GEORGIA (GA)						
U GA-Athens	9	1995	6	1997	1.89	1.50
HAWAII (HI)						
U HI-Manoa	5	1989	4	1989	-0.65	1.25
ILLINOIS (IL)						
Northern IL U	6	1996	3	1995	-1.75	2.00
Southern IL U	4	1998	2	1996	-1.75	2.00
U IL-Urbana	3	1991	2	1991	0.33	1.50

Table 14. List of PhD-Granting Institutions with the Gender Ratio for Each (continued).

	Male		Female			
	N	Mean Year of PhD	N	Mean Year of PhD	Difference Year of PhD	Ratio M/F
INDIANA (IN)						
IN State U	11	1995	8	1996	1.28	1.38
IN U-Bloomington	2	1995	3	1990	-4.17	0.67
IOWA (IA)						
U IA-Iowa City	5	1991	2	1997	6.40	2.50
KANSAS (KS)						
KS State U	2	1994	2	1995	1.00	1.00
U KS-Lawrence	13	1994	4	1996	1.60	3.25
KENTUCKY (KY)						
U KY-Lexington	5	1993	6	1999	5.90	0.83
LOUISIANA (LA)						
LA State U	14	1992	6	1991	-1.36	2.33
MARYLAND (MD)						
Johns Hopkins U	7	1979	4	1980	0.57	1.75
U MD-College Park	11	1994	4	1990	-4.59	2.75
MASSACHUSETTS (MA)						
Boston U	9	1989	4	1989	-0.17	2.25
Clark U	6	1997	5	1993	-4.30	1.20
U MA-Amherst	4	1990	3	1993	2.75	1.33
MICHIGAN (MI)						
MI State U	15	1993	14	1994	1.17	1.07
MINNESOTA (MN)						
U MN-Twin Cities	5	1996	2	1995	-0.90	2.50
MISSOURI (MO)						
U MO-Kansas City	7	1993	4	1993	-0.43	1.75
NEBRASKA (NE)						
U NE-Lincoln	4	1992	4	1993	0.75	1.00
NEVADA (NV)						
U NV-Reno	5	1998	2	1997	-1.00	2.50

Table 14. List of PhD-Granting Institutions with the Gender Ratio for Each (continued).

	Male		Female			
	N	Mean Year of PhD	N	Mean Year of PhD	Difference Year of PhD	Ratio M/F
NEW JERSEY (NJ)						
Montclair State U	8	1998	3	1998	0.04	2.67
Rutgers U	17	1988	10	1988	-0.06	1.70
NEW YORK (NY)						
CUNY-Graduate Center	12	1990	14	1993	2.81	0.86
U Buffalo-State U NY	9	1995	7	1995	0.22	1.29
Syracuse U	6	1997	5	1999	1.97	1.20
NORTH CAROLINA (NC)						
U NC-Chapel Hill	5	1998	2	1997	-0.60	2.50
U NC-Charlotte	4	2001	3	2002	1.58	1.33
UNC-Greensboro	4	1998	2	1998	-0.75	2.00
OHIO (OH)						
Kent State U	2	1998	2	2002	4.00	1.00
Ohio State U	14	1990	8	1994	4.54	1.75
U Cincinnati	5	1987	2	1990	2.90	2.50
U Toledo	4	1996	2	1999	3.33	2.00
OKLAHOMA (OK)						
OK State U	3	1999	3	2003	3.67	1.00
U OK-Norman	3	1994	2	1993	-1.00	1.50
OREGON (OR)						
OR State U	13	1991	6	1991	0.46	2.17
U OR-Eugene	5	1990	4	1991	0.70	1.25
Portland State U	2	1989	2	1988	-1.50	1.00
PENNSYLVANIA (PA)						
PA State U	11	1988	7	1993	4.47	1.57
U PA-Philadelphia	8	1980	8	1980	-0.63	1.00
SOUTH CAROLINA (SC)						
U SC-Columbia	5	2000	6	1997	-3.00	0.83
TENNESSEE (TN)						
U TN-Knoxville	2	1982	2	1986	4.00	1.00

Table 14. List of PhD-Granting Institutions with the Gender Ratio for Each (continued).

	Male		Female			
	N	Mean Year of PhD	N	Mean Year of PhD	Difference Year of PhD	Ratio M/F
TEXAS (TX)						
TX A&M U	12	1999	5	1998	-0.92	2.40
TX State U	13	1994	3	1992	-1.67	4.33
U TX-Austin	7	1990	7	2000	9.71	1.00
U TX-Dallas	3	1992	1	1992	0.33	3.00
TX Tech U	2	1998	1	2002	4.50	2.00
UTAH (UT)						
U UT-Salt Lake City	3	2000	2	2000	0.33	1.50
UT State U	9	1991	4	1992	1.25	2.25
VIRGINIA (VA)						
George Mason U	11	1995	5	1996	1.75	2.20
VA Tech U	2	1985	3	2003	18.00	0.67
WASHINGTON (WA)						
U WA-Seattle	5	1991	5	1991	0.20	1.00
WEST VIRGINIA (WV)						
WV U-Morgantown	6	1989	3	1988	-0.83	2.00
WISCONSIN (WI)						
U WI-Madison	11	1994	3	1994	-0.13	3.67
U WI-Milwaukee	4	1994	4	1995	0.90	1.00

Mean Year of PhD is the mean of the years when the professor's PhD was granted.
Difference Year of PhD is the mean difference in the year PhD was granted, women minus men, for each institution.
M/F Ratio is the ratio of the number of male to female professors

Table 16. Descriptive Statistical Properties of Variables.

DEMOGRAPHIC VARIABLES

	Male			Female			Total		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Age (at PhD)†	32.2	4.25	280	33.1	5.09	177	32.6	4.61	457
Gender	61.3%		533	38.7%		336			869
Race:*									
White	83.6%		236	79.9%		143	82.2%		379
Black	2.2%		6	2.8%		5	2.4%		11
Asian	9.3%		26	13.9%		25	11.1%		51
Hispanic	3.6%		10	2.8%		5	3.3%		15
Other	1.1%		3	1.1%		2	1.1%		5
Total	100%		281	100%		180	100%		461
Region+									
South	31.9%		170	32.5%		109	32.1%		279
West	20.4%		109	19.0%		64	19.9%		173
North East	21.6%		115	24.1%		81	22.5%		196
Lakes	15.2%		81	15.8%		53	15.5%		134
Plains	10.9%		58	8.6%		29	10.0%		87
Total	100%		533	100%		336	100%		869
Born:◦									
In US	70.2%		198	67.6%		121	69.2%		319
Not US	29.8%		84	32.4%		58	30.8%		142
Total	100%		282	100%		179	100%		461

† For age when PhD Granted: t-test: t = 2.047, df = 452, p = 0.0412, distribution skewed toward larger values, Wilcoxon rank sum test, z = 1.510, p = 0.1311

* For race: χ^2 = 2.80, df = 4, p = 0.591.

+ For region: χ^2 = 1.90, df = 4, p = 0.755.

◦ For birth place: χ^2 = 0.351, df = 1, p = 0.553.

Table 16. Descriptive Statistical Properties of Variables (continued).

EMPLOYMENT VARIABLES

	Men			Women			Total		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Year of PhD[*]	1992.3	8.6	533	1993.5	8.8	336	1992.8	8.7	869
PhD Cohort[≠]									
PhD < 1989	64.2%		179	35.8%		100	32.2%		279
PhD 89-97	64.6%		181	35.4%		99	32.3%		280
PhD > 1997[≠]	55.7%		171	44.3%		136	35.5%		307
Top Rank PhD[^]	9.3%		533	37.8%		336	32.6%		869
Years PhD to Hire[❣]	4.10	5.2	533	3.66	5.0	336	3.92	5.1	869
Inbreed[+]	4.9%		533	4.8%		336	4.8%		869
Top Rank AssP[⌂]	16.5%		533	16.7%		336	16.6%		869
Hours Spent:[◊]									
Total	50.4	10.7	282	48.6	9.7	179	49.7	10.3	461
Teaching	13.3	7.7	282	13.6	7.3	179	13.4	7.5	461
Research	20.4	11.1	280	17.7	10.2	178	19.3	10.8	461
Admin	12.5	11.1	281	11.9	12.2	178	12.3	11.6	459
Other	4.2	5.8	281	5.4	6.4	178	4.7	6.1	459
Years to Promotion:									
PhD to Assoc, Prof[†]	8.1	3.1	518	8.5	3.1	330	8.3	3.1	848
PhD to Full Prof[•]	14.5	4.4	336	15.7	4.9	164	14.9	4.6	500
Tenure Granted[◙]	97.2%		281	95.6%		180	96.5%		461
Assistant Professor Moves:									
Total[∩]	0.246	.0477	533	0.280	0.567	336	0.259	0.513	869
To PhD-granting[‡]	0.285	0.452	533	0.256	0.437	336	0.274	0.446	869
Promotion Gained[Ω]	0.120	0.325	533	0.0833	0.277	336	0.106	0.308	869

Table 16. Descriptive Statistical Properties of Variables (continued).

EMPLOYMENT VARIABLES (continued)

	Men			Women			Total		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Speciality (%)▲									
GIS○	21.2	32.7	279	12.4	26.8	174	17.8	30.9	453
Human□	23.6	35.1	279	23.9	36.2	174	23.7	35.5	453
Physical■	23.9	36.7	279	21.5	37.0	174	23.0	36.8	453
Regional♦	4.9	13.7	279	3.7	10.4	174	4.5	12.5	453
Other△	26.4	38.2	279	38.5	44.3	174	30.7	41.0	453

* For year of PhD: distribution skewed, Wilcoxon rank sum test, z = 2.341, p = 0.0192.

^ For PhD from top ranked program: χ^2 = 6.82, df = 1, p = 0.009.

≠ For all PhD cohorts: χ^2 = 6.34, df = 2, p = 0.042; for individual cohorts only > 1997 cohort significantly different with Wilcoxon rank sum test, z = 2.513, p = 0.012.

ᴥ For years between PhD-granting and hiring as an assistant professor: t = 1.213, df = 867, p = 0.226; distribution skewed, Wilcoxon rank sum test, z = 1.548, p = 0.122.

+ For inbreed: χ^2 = 0.006, df = 1, p = 0.938.

⌂ For hired by top-ranked institution when assistant professor: χ^2 = 0.0036, df = 1, p = 0.952.

◊ For total hours spent: Wilcoxon rank sum test, z = 1.995, p = 0.0460; teaching: Wilcoxon rank sum test, z = 0.725, p = 0.4687; research: Wilcoxon rank sum test, z = 2.559, p = 0.0105; administrative: Wilcoxon rank sum test, z = 1.300, p = 0.1934; other: Wilcoxon rank sum test, z = 2.168, p = 0.0301.

† Years from award of PhD to promotion to associate professor: t = 1.93, df = 846, p = 0.0545; distribution skewed, Wilcoxon rank sum test, z = 1.846, p = 0.0649.

• Years from award of PhD to promotion to professor: t = 2.85, df = 498, p = 0.0046; distribution skewed, Wilcoxon rank sum test, z = 2.722, p = 0.0065.

◙ For tenure granted: Wilcoxon rank sum test, z = 0.913, p = 0.3611.

∩ For number of assistant professor moves: χ^2 = 5.71, df = 3, p = 0.126; Wilcoxon rank sum test, z = 0.266, p = 0.790.

‡ For moves to PhD-granting institution: χ^2 = 0.885, df = 1, p = 0.347; Wilcoxon rank sum test, z = 0.940, p = 0.3471.

Ω For promotion moves: χ^2 = 2.94, df = 1, p = 0.086; Wilcoxon rank sum test, z = 1.713, p = 0.0866.

▲ For speciality: χ^2 = 17.7, df = 4, p = 0.00144;

○ For GIS: χ^2 = 9.43, df = 1, p = 0.002 medians test; Wilcoxon rank sum test, z = 3.238, p = 0.0012.

□ For human: χ^2 = 0.578, df = 1, p = 0.447 medians test. Wilcoxon rank sum test, z = 0.398, p = 0.6908.

■ For physical: χ^2 = 6.91, df = 1, p = 0.0.009 medians test; Wilcoxon rank sum test, z = 1.991, p = 0.0465.

♦ For regional: χ^2 = 1.83, df = 1, p = 0.177 medians test. Wilcoxon rank sum test, z = 1.395, p = 0.1630.

△ For other: χ^2 = 3.79, df = 1, p = 0.051 medians test. Wilcoxon rank sum test, z = 2.616, p = 0.0089.

Table 16. Descriptive Statistical Properties of Variables (continued).

PRODUCTIVITY VARIABLES

	Men			Women			Total		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Publications:									
Start AssP‡	2.0	2.8	533	1.1	1.5	336	1.7	2.4	869
Before AscP*	14.9	16.7	518	10.7	8.8	330	13.3	14.3	848
Before Prof+	29.3	31.4	336	21.6	16.0	164	26.7	27.5	500
Citations:									
Start AssP⌂	58.2	157	533	25.2	64.3	336	45.5	130.2	869
Before AscP†	375.2	622	518	219.2	348.9	330	314.5	537.7	848
Before Prof◊	678.4	928	336	508.8	899.2	164	622.8	920.9	500
Grants:									
Received♦	92.9%		283	92.8%		180	92.8%		463
Amount ($M)○	3.43	5.63	254	1.94	3.47	154	2.87	4.96	408
Amount $M/Yr△	0.323	0.504	252	0.203	0.307	154	0.277	0.443	406
Over Years▲	10.4	6.0	252	9.10	5.38	153	9.91	5.83	405

‡ Publications when hired as assistant professor: $t = 6.04$, $df = 852$, $p < 0.00005$; distribution skewed, Wilcoxon rank sum test, $z = 4.187$, $p < 0.00005$.
* Publications before promotion to associate professor: $t = 4.29$, $df = 867$, $p < 0.00005$; distribution skewed, Wilcoxon rank sum test, $z = 4.777$, $p < 0.00005$.
+ Publications before promotion to professor: $t = 2.95$, $df = 499$, $p = 0.0033$; distribution skewed, Wilcoxon rank sum test, $z = 3.712$, $p = 0.0002$.
⌂ Citations when hired as assistant professor: $t = 3.66$, $df = 867$, $p < 0.0003$; distribution skewed, Wilcoxon rank sum test, $z = 3.039$, $p = 0.0024$.
† Citations before promotion to associate professor: $t = 4.16$, $df = 846$, $p < 0.00005$; distribution skewed, Wilcoxon rank sum test, $z = 4.650$, $p < 0.00005$.
◊ Citations before promotion to professor: $t = 1.94$, $df = 498$, $p = 0.053$; distribution skewed, Wilcoxon rank sum test, $z = 2.459$, $p = 0.0139$.
•Note publication and citation count starts five years before PhD granted.
♦ For grant or contract received: $\chi^2 = 0.004$, $df = 1$, $p = 0.95$.
○ For amount ($): median, $\chi^2 = 2.43$, continuity corrected, $df = 1$, $p = 0.119$.
△ For amount ($)/year: median, $\chi^2 = 3.74$, continuity corrected, $df = 1$, $p = 0.053$.
▲For over years: $t = 2.07$, $df = 404$, $p = 0.0389$.

Table 16. Descriptive Statistical Properties of Variables (continued).

FAMILY VARIABLES

	Men			Women			Total		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Marital status:*									
Legal+	88.1%		245	73.2%		128	2.3%		373
Partner◊	5.4%		15	10.3%		18	7.3%		33
Single♦	5.4%		15	13.1%		23	8.4%		38
Never○	1.0%		3	3.4%		6	2.0%		9
Total	100%		278	100%		175	100%		453
Spouse Works: △									
Full-time▲	58.6%		153	78.6%		114	65.7%		267
Part time•	21.1%		55	11.7%		17	17.7%		72
Hours†	20.3	7.50	53	17.1	11.4	18	19.4	8.69	71
No work■	20.3%		53	9.7%		14	16.5%		67
Spouse Works:□									
University	16.0%		41	14.9%		21	15.6%		62
My University	17.2%		44	17.7%		25	17.4%		69
My Department	7.4%		19	16.1%		21	10.1%		40
Not University	59.4%		152	52.5%		76	56.9%		228
Total	100%		256	100 %		143	100%		399

* For marital status: χ^2 = 17.1, df = 3, p = 0.001.
+ For legal: χ^2 = 16.6, df = 1, p < 0.0005.
◊ For partner: χ^2 = 3.80, df = 1, p = 0.051.
♦ For single: χ^2 = 8.39, df = 1, p = 0.004.
○ For never: χ^2 = 3.04, df = 1, p = 0.081.
△ For spouse/partner works: χ^2 = 16.7, df = 2, p = 0.0005.
▲For spouse/partner works full-time: χ^2 = 15.1, df = 1, p < 0.0005.
• For spouse/partner works part time: χ^2 = 5.72, df = 1, p = 0.017.
† For hours worked part time: t = 1.34, df = 69, p = 0.185; Wilcoxon rank sum test, z = 0.888, p = 0.3746.
■ For spouse/partner not working: χ^2 = 7.82, df = 1, p = 0.005.
□ For spouse/partner works at university: χ^2 = 6.16, df = 3, p = 0.104.

Table 16. Descriptive Statistical Properties of Variables (continued).

PROGENY VARIABLES

	Men			Women			Total		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Early Baby:									
Present[*]	48.4%		246	48.9%		139	48.6%		385
Number[+]	0.663	0.769	246	0.633	0.724	139	0.652	0.752	385
CHILDREN									
While AscP:									
Number[†]	1.15	1.08	243	1.07	0.859	137	1.12	1.01	380
< Age 6[○]	1.05	1.03	243	0.941	0.802	137	1.01	0.951	380
> Age 6[•]	0.107	0.347	243	0.131	0.417	137	0.116	0.374	380
While Prof:									
Number[◙]	1.61	1.02	159	1.34	0.924	68	1.53	1.00	227
< Age 6[□]	1.09	1.01	159	0.926	0.919	68	1.04	0.986	227
> Age 6[■]	0.579	1.17	159	0.412	0.674	68	0.528	1.05	227
Caregiver[♦]	7.6%		237	11.5%		130	9.0%		367

[*] For baby born in five years after PhD: $\chi^2 = 0.106$, df = 1, p = 0.918.
[+] For number early babies: t = 0.369, df = 383, p = 0.712; distribution skewed, Wilcoxon rank sum test, z = 0.174, p = 0.862.
[†] For number of children while associate professor: t = 0.804, df = 378, p = 0.422; distribution skewed, Wilcoxon rank sum test, z = 0.426, p = 0.6702.
Note some professors were never associate professors.
[○] For number of children under age 6 while associate professor: t = 1.02, df = 374, p = 0.320. distribution skewed, Wilcoxon rank sum test, z = 0.549, p = 0.5833.
[•] For number of children from age 6 to 18 while associate professor: t = 0.611, df = 378, p = 0.542; distribution skewed, Wilcoxon rank sum test, z = 0.285, p = 0.7758.
[◙] For number of children while professor: t = 1.88, df = 225, p = 0.0608. distribution skewed, Wilcoxon rank sum test, z = 1.695, p = 0.0900.
[□] For number of children under age 6 while professor: t = 1.18, df = 225, p = 0.241. distribution skewed, Wilcoxon rank sum test, z = 1.050, p = 0.2935.
[■] For number of children between age 6 and 18 while professor: t = 1.10, df = 225, p = 0.273. distribution skewed, Wilcoxon rank sum test, z =0.575 , p = 0.5651.
[♦] For caregiver: $\chi^2 = 1.60$, df = 1, p = 0.207.

Table 16. Descriptive Statistical Properties of Variables (continued).

JOB SEARCH AND VOTING VARIABLES

	Men		Women		Total	
	Mean	N	Mean	N	Mean	N
Job Search:+						
No Limitation	75.5%	213	56.2%	100	68.0%	313
Limitation	24.5%	69	43.8%	78	32.0%	147
Total	100%	282	100%	178	100%	460
Vote:*						
Democratic○	69.8%	187	82.3%	135	74.5%	322
Republican◊	4.5%	12	2.4%	4	3.7%	16
No Preference□	25.7%	70	15.3%	25	21.8%	95
Total	100%	269	100%	164	100%	433

+ For geographical job search limitations: $\chi^2 = 18.8$, df = 1, $p < 0.0005$.
* For vote: $\chi^2 = 8.45$, df = 2, $p = 0.015$.
○ For democratic vote: $\chi^2 = 8.76$, df = 1, $p = 0.003$.
◊ For republican vote: $\chi^2 = 1.17$, df = 1, $p = 0.279$.
□ For no preference vote: $\chi^2 = 6.91$, df = 1, $p = 0.009$.

Table 18. Ranking of Variables with ≥10:1 Events per Variable Ratio by Univariate p-Value.

Associate Professors (N = 848 and 34 variables)

	Total Number	Number with Event	Univariate p-Value	Events per 15 Variables
Geography	848	509	<0.0005	
PhDHire	848	848	<0.0005	
AscP Pubs	848	848	<0.0005	
AscP Citations	848	848	0.001	
AssP Moves Number	848	194	0.001	12.9
AssP Moves to PhD Grant	848	229	0.002	
Focus Human Geog (%)	449	194	0.002	12.9
HirePubs	848	848	0.003	
PhD Cohort 89-97	845	280	0.01	
PhD Cohort > 1997	845	307	0.029	
Vote Democrat	424	315	0.059	
Years Grant	398	398	0.064	
Work Hours Admin	447	413	0.081	
Focus Physical Geog (%)	450	275	0.102	
Focus: Other (%)	270	195	0.142	
Region New England	848	193	0.151	12.9
Gender	848	336	0.162	
Top PhD	845	283	0.212	
Year of PhD	848	869	0.288	
US Birth	450	312	0.305	
South	848	276	0.327	
Total Work Hours	449	449	0.329	
Grant Amount	400	400	0.351	
Work Hours Other	447	234	0.499	
Early Baby Number	376	185	0.535	
TopAssP	848	144	0.543	
ChildTotalAscP	375	249	0.563	
HireCites	848	848	0.600	
PhD Cohort <1989	845	279	0.621	
Contract/Grant	452	420	0.634	
White	451	370	0.649	
Early Baby Dummy	376	183	0.664	
Hours Research	449	441	0.787	
Child< 6yrsAscP	375	233	0.818	
Hours Teaching	449	426	0.867	
DolYr	397	397	0.881	
Hiring Institution Code	848	848	0.910	
Legal Marriage	443	364	0.917 (38)	

Table 18. Ranking of Variables with ≥10:1 Events per Variable Ratio by Univariate p-Value (continued).

<u>Full Professors</u> (N = 499 with 37 variables)

	Total Number	Number with Event	Univariate p-Value	Events per 15 Variables
Hire Pubs	499	266	<0.0005	
Years PhD to Hired	499	499	<0.0005	
Hire Citations	499	236	<0.0005	
Race: White	271	220	0.011	
Gender	499	164	0.018	
AscP Citations	485	485	0.022	
Focus Other (%)	269	269	0.037	
Geography	499	294	0.089	
Grant Amt	249	248	0.092	
Spouse Full-time Work	241	147	0.115	12.3
Prof Citations	499	485	0.115	
ChildTotalAscP	221	146	0.148	12.2
Early Baby Dummy	226	114	0.155	
Hrs Administration	269	254	0.188	
Grant Amt/Year	246	245	0.231	
Early Baby Number	226	115	0.246	
Focus Physical	270	269	0.251	
Vote Democratic	259	193	0.259	
Child< 6yrsAscP	221	138	0.275	
West	499	120	0.284	13.3
Spouse No Work	241	240	0.290	
Hours Teaching	271	250	0.306	
Legal Marriage	265	222	0.339	
Number AssP Moves	499	111	0.361	
Total Hours	271	271	0.398	
NorthEast	499	121	0.399	
Move to PhD-Granting	499	148	0.426	
Grant Years	249	245	0.483	
Regional Geog	269	269	0.492	
US Birth	272	187	0.521	
Contract or Grant	272	260	0.547	
AscP Publications	485	464	0.578	
Prof Publications	499	499	0.583	
ChildTotalProf	225	179	0.619	
Hours Other	270	144	0.779	
South	499	136	0.939	
Time Research	271	264	0.989 (37)	

Table 18. Ranking of Variables with ≥10:1 Events per Variable Ratio by Univariate p-Value (continued).

Number is sample size, p-value from Cox regression for variable, number of events per variable is number with trait divided by the number of variables. Only the smallest events-per-variable ratios are shown.

Table 26. Stratified Cox Regression Model Selected for Univariate p-Values ≤ 0.01.

Associate Professors

Stratified Cox regr. -- Breslow		method	for	ties		
No. of subjects =	449			Number of obs =		449
No. of failures =	449					
Time at risk =	3728					
				LR chi2(9) =		124.84
Log likelihood =	-1351.1314			Prob > chi2 =		0.00005

_t	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
PhDHire (1)	-2.03136	0.316991	-6.41	<0.0005	-2.65265	-1.41007
PhDHire (2)	0.249248	0.062686	3.98	<0.0005	0.126386	0.372111
HirPubs	0.127905	0.026993	4.74	<0.0005	0.075	0.180811
AscPPubs	-0.02423	0.007077	-3.42	0.001	-0.0381	-0.01036
NumMoves	-0.36395	0.127379	-2.86	0.004	-0.61361	-0.1143
Geog	0.302344	0.114708	2.64	0.008	0.077521	0.527167
Human	0.001748	0.00152	1.15	0.250	-0.00123	0.004727
CitAscP	0.000109	0.00014	0.78	0.435	-0.00016	0.000383
MovePhD	0.080749	0.14899	0.54	0.588	-0.21127	0.372764
Stratified	by	Gender	TopAssP	PhD89	PhD8997	PhD97

Table 26. Stratified Cox Regression Model Selected for Univariate p-Values ≤ 0.03 (continued)

Professors

Stratified Cox regr. -- Breslow method for ties

No. of subjects =	261	Number of obs =	261
No. of failures =	260		
Time at risk =	4005		
		LR chi2(6) =	25.25
Log likelihood =	-492.59001	Prob > chi2 =	0.0003

_t	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
PhDHire(1)	-1.89969	0.545597	-3.48	<0.0005	-2.96904	-0.83034
PhDHire(2)	0.533385	0.154805	3.45	0.001	0.229973	0.836798
PhD89	-0.11341	.	.	.	.	.
White	-0.3883	0.206744	-1.88	0.060	-0.79351	0.016909
HirePubs	0.147878	0.052791	2.8	0.005	0.044409	0.251347
Gender	0.4627	.	.	.	.	.
CitAscP	-0.0002	0.000222	-0.89	0.371	-0.00063	0.000236
HirCites	-0.00099	0.001168	-0.84	0.398	-0.00328	0.001303
Stratified	by	Gender	TopAssP	PhD89	PhD8997	PhD97

Table 28. Gender Specific Coefficients for Male and Female Associate Professors

Male

Cox regression -- exact partial		likelihood	
No. of subjects =	272	Number of obs =	272
No. of failures =	272	LR chi2(9) =	125.33
Time at risk =	2197	Prob > chi2 =	<0.00005
Log likelihood =	-577.531		

_t	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
PhDHire(1)	-19.6858	4.159852	-4.73	<0.0005	-27.839	-11.5327
PhDHire(2)	7.693704	1.757611	4.38	<0.0005	4.248851	11.13856
HirePubs	0.202069	0.038125	5.3	<0.0005	0.127345	0.276794
AscPPubs	-0.04433	0.010319	-4.3	<0.0005	-0.06456	-0.0241
NumMoves	1.115985	0.282629	3.95	<0.0005	0.562044	1.669927
Geog	0.452502	0.167395	2.7	0.007	0.124413	0.780591
Human	0.003389	0.002251	1.51	0.132	-0.00102	0.007801
MovePhD	0.10724	0.22201	0.48	0.629	-0.32789	0.542371
CitAscP	0.00014	0.000175	0.8	0.425	-0.0002	0.000483

Table 28. Gender Specific Coefficients for Male and Female Associate Professors (continued).

Female

Cox regression -- exact partial			likelihood			
No. of subjects =		174		Number of obs =		174
No. of failures =		174		LR chi2(9) =		81.11
Time at risk =		1506		Prob > chi2 =		<0.00005
Log likelihood =	-341.11035					

_t	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
PhDHire(1)	-26.1513	5.22687	-5	<0.0005	-36.3958	-15.9069
PhDHire(2)	9.699584	2.143111	4.53	<0.0005	5.499163	13.90001
HirePubs	0.141079	0.079616	1.77	0.076	-0.01497	0.297124
AscPPubs	-0.04912	0.018089	-2.72	0.007	-0.08458	-0.01367
NumMoves	0.502959	0.429964	1.17	0.242	-0.33975	1.345672
Geog	0.146659	0.215404	0.68	0.496	-0.27553	0.568844
Human	0.00566	0.002844	1.99	0.047	0.000087	0.011233
MovePhD	0.20161	0.3245	0.62	0.534	-0.4344	0.837618
CitAscP	0.000739	0.000485	1.52	0.128	-0.00021	0.001689

Table 29. Gender Specific Coefficients for Male and Female Full Professors.

Male

Cox regression --	exact partial	likelihood		
No. of subjects =	175		Number of obs =	175
No. of failures =	174			
Time at risk =	2635			
			LR chi2(6) =	24.92
Log likelihood =	-442.531		Prob > chi2 =	0.0004

_t	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
HirePubs	0.201653	0.050884	3.96	<0.0005	0.101923	0.301383
White	-0.62823	0.226468	-2.77	0.006	-1.0721	-0.18436
FocusOth	-0.00365	0.002432	-1.5	0.134	-0.00842	0.001118
HireCites	-0.00141	0.001102	-1.28	0.201	-0.00357	0.000751
CitAscP	-5.7E-05	0.000207	-0.28	0.782	-0.00046	0.000348
PhDHire	-0.00219	0.016959	-0.13	0.897	-0.03542	0.031053

Table 29. Gender Specific Coefficients for Male and Female Full Professors (continued).

Female

Cox regression --	exact partial	likelihood				
No. of subjects =		84		Number of obs =		84
No. of failures =		84				
Time at risk =		1335				
				LR chi2(6) =		8.21
Log likelihood =		-189.21		Prob > chi2 =		0.2234

_t	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
HirePubs	-0.00926	0.124016	-0.07	0.94	-0.25233	0.233806
White	-0.39113	0.325329	-1.2	0.229	-1.02876	0.246504
FocusOth	-0.00012	0.003066	-0.04	0.969	-0.00613	0.005892
HireCites	0.008045	0.00494	1.63	0.103	-0.00164	0.017728
CitAscP	1.17E-06	0.000526	0.00	0.998	-0.00103	0.001031
PhDHire	-0.03135	0.022684	-1.38	0.167	-0.0758	0.013115

REFERENCES

Ahern, N. C. and E. L. Scott. 1981. *Career Outcomes in a Matched Sample of Men and Women PhDs: An Analytical Report*. Washington, DC: National Academy Press.

Alpert, D. 1989. Gender Inequality in Academia: An Empirical Analysis. *Journal of Higher Education* 52 No. 2: 9-14.

Ames, B., D. C. Barker, C. W. Bonneau, and C. J. Carman. 2005. Hide the Republicans, the Christians, and the Women: A Response to "Politics and Professional Advancement Among College Faculty." *Forum* 3 No. 2: Article 7.

Anonymous. 1933. Damages: Calculation of Present Value of Future Salary Payments. *Columbia Law Review* 33 No. 7: 1255-1257.

Anonymous. 1979. Academic Freedom and Federal Regulation of University Hiring. *Harvard* Law *Review* 92 No. 4: 879-897.

Anonymous. 1980. Title VI, Title IX, and the Private University: Defining "Recipient" and "Program or Part Thereof." *Michigan Law Review* 78 No. 4: 608-625.

Astin, H. S. 1972. Employment and Career Status of Women Psychologists. *American Psychologist* 27 No. 5: 371-381.

Astin, H. S. and A. E Bayer. 1972. Sex Discrimination in Academe. *Educational Record* 53 No. 2:101-118.

Astin, H. S. and J. F. Milem. 1997. The Status of Academic Couples in U.S. Institutions. In *Academic Couples: Problems and Promises*, ed. by M. A. Ferber and J. W. Loeb. Chicago, IL: University of Illinois Press, 128-155.

Barnshaw, J. and S. Dunietz. 2015. Busting the Myths: The Annual Report on the Economic Status of the Profession, 2014-15. *Academe* 101 No. 2: 4-19.

Bayer, A. E. 1973. *Teaching Faculty in Academe: 1972-73*. Washington, DC: American Council on Education.

Bayer, A. E. and H. S. Astin. 1968. Sex Differences in Academic Rank and Salary among Science Doctorates in Teaching. *Journal of Human Resources* 3 No. 2: 191-200.

Bayer, A. E. and H. S. Astin. 1975. Sex Differentials in Academic Reward System. *Science* 188 No. 4190: 796-802.

Becker, G. S. 1993. *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*. 3rd ed. Chicago, IL: University of Chicago Press.

Bernard, J. 1966. *Academic Women*. Cleveland, OH: Meridian Books.

Bird, R. C. 1997. More than a Congressional Joke: A Fresh Look at the Legislative History of Sex Discrimination of the 1964 Civil Rights Act. *William and Mary Journal of Women and the Law* 3 No.1: 137-161.

Bishop, G., H. Beebee, E. Goddard, and A. Rini. 2013. Seeing the Trends in the Data. In *Women in Philosophy: What Needs to Change*?, eds. K. Hutchinson and F. Jenkins. New York, NY: Oxford University Press, 231-252.

Box-Steffensmeier, J. M. and B. S. Jones. 2004. *Event History Modeling: A Guide for Social Scientists*. New York, NY: Cambridge University Press.

Burstein, P. 1991. "Reverse Discrimination" Cases in the Federal Courts: Legal Mobilization by a Countermovement. *Sociological Quarterly* 32 No. 4: 511-528.

Byrne, J. P. 1989. Academic Freedom: A "Special Concern of the First Amendment." *Yale Law Journal* 99 No. 2: 251-340.

Cardiff, C. F. and D. B. Klein. 2005. Faculty Partisan Affiliations in All Disciplines: A Voter-Registration Study. *Critical Review* 17 No. 3/4: 237-255.

Cataldi, E.F., E. M. Bradburn, M. Fahimi, and L. Zimbler. 2005. *2004 National Study of Postsecondary Faculty (NSOPF:04): Background Characteristics, Work Activities, and Compensation of Instructional Faculty and Staff: Fall 2003* (NCES 2006-176). U.S. Department of Education. Washington, DC: National Center for Education Statistics, http://eric.ed.gov/?id=ED489118 (accessed November 2, 2015).

Ceci, S. J., D. K. Ginther, S. Kahn, and W. M. Williams. 2014. Women in Academic Science: A Changing Landscape. *Psychological Science in the Public Interest* 15 No. 3: 75-141.

CEEWISE (Committee on the Education and Employment of Women in Science and Engineering). 1979. *Climbing the Academic Ladder: Doctoral Women Scientists in Academe: A Report to the Office of Science and Technology Policy*. Washington, DC: National Academies Press.

Chase, M. 2007. Gender Discrimination, Higher Education, and the Seventh Circuit: Balancing Academic Freedom with Protections under Title VII, Case Note: *Farrell vs. Butler University*. *Wisconsin Women's Law Journal* 22 No. 1: 153-176.

Cleves, M., W. Gould, R. G Gutierrez, and Y. V. Marchenko. 2010. *An Introduction to Survival Analysis Using Stata*. 3rd ed. College Station, TX: Stata Press.

Cole, J. R. and H. Zuckerman. 1984. The Productivity Puzzle: Persistence and Change in Patterns of Publication of Men and Women Scientists. *Advances in Motivation and Achievement* 2: 217-258.

Daniel, W. W. 1990. *Applied Nonparametric Statistics*. 2nd ed. Pacific Grove, CA: Duxbury.

Dekat, G. S. 2009. John Jay, Discrimination, and Tenure. *Scholar: St. Mary's Law Review on Minority Issues* 11: 237-279.

Dillman, D. A., J. D. Smyth, and L. M. Christian. 2009. *Internet, Mail, and Mixed-Mode Surveys: The Tailored Design Method*. 3rd ed. Hoboken, NJ: John Wiley and Sons, Inc.

Dubben, H.-H. and H.-P. Beck-Bornholdt. 2005. Systematic Review of Publication Bias in Studies on Publication Bias. *British Medical Journal* 331 No. 7514: 433-434.

Evans, S. 2003. Commentary: Matched Cohorts Can Be Useful. *British Medical Journal* 326 No. 7385: 360.

Feinberg, W. E. 1984. At a Snail's Pace: Time to Equality in Simple Models of Affirmative Action Programs. *American Journal of Sociology* 90 No. 1: 168-181.

Ferber, M. A. and C. A. Green. 1982. Traditional or Reverse Sex Discrimination? A Case Study of a Large Public University. *Industrial and Labor Relations Review* 35 No. 4: 550-564.

Finkelstein, M. O. 1980. The Judicial Reception of Multiple Regression Studies in Race and Sex Discrimination Cases. *Columbia Law Review* 80 No. 4: 737-754.

Firmin, P. A., S. S. Goodman, T. E. Hendricks, and J. J. Linn. 1968. University Cost Structure and Behavior: An Empirical Study. *Journal of Accounting Research* 6: 122-155.

Flygare, T. J. 1984. Faculty Salaries: The Battle between Affirmative Action and Reverse Discrimination in Higher Education. *Phi Delta Kappan* 65 No. 7: 500-501.

Foote, K. E. and M. N. Solem. 2009. Toward Better Mentoring for Early Career Faculty: Results of a Study of US Geographers. *International Journal for Academic Development* 14, No. 1: 47–58.

Fox, M. F. 2005. Gender, Family Characteristics, and Publication Productivity among Scientists. *Social Studies of Science* 35 No. 1: 131-150.

Fox, M. F. and C. A. Faver. 1985. Men, Women, and Publication Productivity: Patterns among Social Work Academics. *Sociological Quarterly* 26 No. 4: 537-549.

Franklin, C. 2012. Inventing the "Traditional Concept" of Sex Discrimination. *Harvard Law Review* 125 No. 6: 1307-1380.

Galles, K. M. 2004. Filling the Gaps: Women, Civil Rights, and Title IX. *Human Rights* 31 No. 3: 16-18.

Ginsburg, R. B. 1973. The Need for the Equal Rights Amendment. *American Bar Association Journal* 59 No. 9: 1013-1019.

Ginther, D. K. 2001. Does Science Discriminate against Women? Evidence from Academia, 1973-97, available at http://www.frbatlanta.org/filelegacydocs/wp0102.pdf (accessed November 7, 2015).

Ginther, D. K. and K. J. Hayes. 2003. Gender Differences in Salary and Promotion for Faculty in the Humanities 1977-95. *Journal of Human Resources* 38 No. 1: 34-73.

Ginther, D. K. and S. Kahn. 2004. Women in Economics: Moving Up or Falling Off the Academic Career Ladder? *Journal of Economic Perspectives* 18 No. 3: 193-214.

Ginther, D. K. and S. Kahn. 2006. Does Science Promote Women? Evidence from Academia, 1973-2001, http://www.nber.org/~sewp/Ginther_Kahn_revised8-06.pdf (accessed November 7, 2015).

Glenn, N. D. 2005. *Cohort Analysis*. 2nd ed. Thousand Oaks, CA: Sage Publications, Inc.

Goodwin, T. H. and R. D. Sauer. 1995. Life Cycle Productivity in Academic Research: Evidence from Cumulative Publication Histories of Academic Economists. *Southern Economic Journal* 61 No. 3: 728-743.

Goulden, M., M. A. Mason, and K. Frasch. 2011. Keeping Women in the Science Pipeline. *Annals of the American Academy of Political and Social Science* 638: 141-162.

Hair Jr., J. F., W. C. Black, B. J. Babin, and R. E. Anderson. 2010. *Multivariate Data Analysis*. 7th ed. Upper Saddle River, NJ: Pearson Prentice Hall.

Hamilton, R. F. and L. L. Hargens. 1993. The Politics of the Professors: Self-Identifications, 1969-1984. *Social Forces* 71 No. 3: 603-627.

Hanna, C. 1988. The Organizational Context for Affirmative Action for Women Faculty. *Journal of Higher Education* 59 No. 4: 390-411.

Hargens, L. L. and G. M. Farr. 1973. An Examination of Recent Hypotheses about Institutional Inbreeding. *American Journal of Sociology* 78 No. 6: 1381-1402.

Hargens, L. L. and J. S. Long. 2002. Demographic Inertia and Women's Representation among Faculty in Higher Education. *Journal of Higher Education* 73 No. 4: 494-517.

Hargens, L. L., J. C. McCann, and B. F. Reskin. 1978. Productivity and Reproductivity: Fertility and Professional Achievement among Research Scientists. *Social Forces* 57 No. 1: 154-163.

Henderson, P. H., J. E. Clarke, and M. A. Reynolds. 1996. *Summary Report 1995: Doctorate Recipients from United States Universities*. Washington, D.C.: National Academy Press.

Hesli, V. L. and J. M. Lee. 2011. Faculty Research Productivity: Why Do Some of Our Colleagues Publish More than Others? *PS: Political Science and Politics* 44 No. 2: 393-408.

Hesli, V. L., J. M. Lee, and S. M. Mitchell. 2012. Predicting Rank Attainment in Political Science: What Else Besides Publications Affects Promotion? *PS: Political Science and Politics* 45 No. 3: 475-492.

Hilmer, C. and M. Hilmer. 2010. Are There Gender Differences in the Job Mobility Patterns of Academic Economists? *American Economic Review* 100, No. 2: 353-357.

Holden, C. 1996. Researchers Find Feminization a Two-Edged Sword. *Science* 271 No. 5257: 1919-1920.

Hora, M. 2001. The Courts and Academia: Tenure Discrimination Claims Against Colleges and Universities. *Journal of Law and Education* 30 No. 2: 349-356.

Hosmer, D. W., S. Lemeshow, and S. May. 2008. *Applied Survival Analysis: Regression Modeling of Time-to-Event Data*. 2nd ed. Hoboken, NJ: John Wiley and Sons, Inc.

Jacobs, J. A. and S. E. Winslow. 2004. The Academic Life Course, Time Pressures, and Gender Inequality. *Community Work and Family* 7 No. 2: 143–161.

Jenkins, R. 1988. Budget Blues for the Nation's Colleges and Universities. *Academe* 74 No. 5: 12-16.

Jüni, P., D. G. Altman, and M. Egger. 2001. Systematic Reviews in Health Care: Assessing the Quality of Controlled Clinical Trials. *British Medical Journal* 323 No. 7303: 42-46.

Kaminski, D. and C. Geisler. 2012. Survival Analysis of Faculty Retention in Science and Engineering by Gender. *Science* 335 No. 6070: 864-866.

Kekes, J. 1993. The Injustice of Strong Affirmative Action. In *Affirmative Action and the University: A Philosophical Inquiry*, ed. S. M. Cahn. Philadelphia, PA: Temple University Press, 144-156.

Kim, J., E. Elliott, and D.-M. Wang. 2003. A Spatial Analysis of County-Level Outcomes in US Presidential Elections: 1988-2000. *Electoral Studies* 22 No. 4: 741-761.

Klein, J. P. and M. L. Moeschberger. 2003. *Survival Analysis: Techniques for Censored and Truncated Data*. 2nd ed. New York, NY: Springer Science+Business Media, Inc.

Kleinbaum, D. G. and M. Klein. 2005. *Survival Analysis: A Self-Learning Text*. 2nd ed. New York, NY: Springer Science+Business Media, LLC.

Kleinbaum, D. G., L. L. Kupper, and H. Morgenstern. 1982. *Epidemiologic Research: Principles and Quantitative Methods*. New York, NY: John Wiley and Sons, Inc.

Kolpin, V. W. and L. D. Singell Jr. 1996. The Gender Composition and Scholarly Performance of Economics Departments: A Test for Employment Discrimination. *Industrial and Labor Relations Review* 49 No. 3: 408-423.

Kramer, D. T. 2001. What Constitutes Reverse or Majority Race or National Origin Discrimination Violative of Federal Constitution or Statutes—Public Employment Cases. *American Law Reports Federal* 168: 1-141.

Krugman, P. and R. Wells. 2013. *Economics*. 3rd ed. New York, NY: Worth Publishers.

Kulis, S. and D. Sicotte. 2002. Women Scientists in Academia: Geographically Constrained to Big Cities, College Clusters, or the Coasts? *Research in Higher Education* 43 No. 1: 1-30.

Ladd Jr., E. C. and S. M. Lipset. 1975. *The Divided Academy: Professors and Politics*. New York, NY: W. W. Norton and Co.

Landes, W. M. and R. A. Posner. 2000. Citations, Age, Fame, and the Web. *Journal of Legal Studies* 29 No. S1: 319-344.

Lazarsfeld, P. F. and W. Thielens Jr. 1958. *The Academic Mind: Social Scientists in a Time of Crisis*. Glencoe, IL: Free Press.

Levin, S. G. and P. E. Stephan. 1998. Gender Differences in the Rewards to Publishing in Academe: Science in the 1970s. *Sex Roles* 38 No. 11/12: 1049–1064.

Lipset, S. M. 1959. American Intellectuals: Their Politics and Status. *Daedalus* 88 No. 3: 460-486.

Lipset, S. M. 1982. The Academic Mind at the Top: The Political Behavior and Values of Faculty Elites. *Public Opinion Quarterly* 46 No. 2: 143-168.

Lipset, S. M. and E. C. Ladd Jr. 1972. The Politics of American Sociologists. *American Journal of Sociology* 78 No. 1: 67-104.

Loeb, J. W., M. A. Ferber, and H. M. Lowry. 1978. The Effectiveness of Affirmative Action for Women. *Journal of Higher Education* 49 No. 3: 218-230.

Loh, D. Y. 1992. A Critical Analysis of Academic Tenure Decisions: The Disparate Treatment Model Under Title VII Examined. *Boston College Third World Law Journal* 12: 389-431.

Long, J. S., ed. 2001. *From Scarcity to Visibility: Gender Differences in the Careers of Doctoral Scientists and Engineers*. Washington, DC: National Academy Press.

Long, J. S., P. D. Allison, and R. McGinnis. 1993. Rank Advancement in Academic Careers: Sex Differences and the Effects of Productivity. *American Sociological Review* 58 No. 5: 703-722.

Luzzadder-Beach, S. and A. Macfarlane. 2000. The Environment of Gender and Science: Status and Perspectives of Women and Men in Physical Geography. *Professional Geographer* 52 No. 3: 407-424.

Macfarlane, A. and S. Luzzadder-Beach. 1998. Achieving Equity Between Women and Men in the Geosciences. *Geological Society of America Bulletin* 110 No. 12: 1590-1614.

Manchester, C. and D. Barbezat. 2013. The Effect of Time Use in Explaining Male–Female Productivity Differences among Economists. *Industrial Relations: Journal of Economy and Society* 52 No.1: 53–77.

Markie, P. J. 1993. Affirmative Action and the Awarding of Tenure. In. *Affirmative Action and the University: A Philosophical Inquiry*, ed. S. M. Cahn. Philadelphia, PA: Temple University Press, 275-285.

Marschke, R., S. Laursen, J. M. Nielsen, and P. Rankin. 2007. Demographic Inertia Revisited: An Immodest Proposal to Achieve Equitable Gender Representation among Faculty in Higher Education. *Journal of Higher Education* 78 No. 1: 1-26.

Marwell, G., R. Rosenfeld, and S. Spilerman. 1979. Geographic Constraints on Women's Careers in Academia. *Science* 205 No. 4412: 1225-1231.

Mason, M. A. and M. Goulden. 2002. Do Babies Matter? The Effect of Family Formation on the Lifelong Careers of Academic Men and Woman. *Academe* 88 No. 6: 21-27.

Mason, M. A. and M. Goulden. 2004. Marriage and Baby Blues: Redefining Gender Equity in the Academy. *Annals of the American Academy of Political and Social Science* 596: 86-103.

McElrath, K. 1992. Gender, Career Disruption, and Academic Rewards. *Journal of Higher Education* 63 No. 3: 269-281.

McGee, R. 1960. The Function of Institutional Inbreeding. *American Journal of Sociology* 65 No. 5: 483-488.

Menard, S. 2002. *Longitudinal Research*. 2nd ed. Thousand Oaks, CA: Sage Publications, Inc.

Merritt, D. J. and B. F. Reskin. 1997. Sex, Race, and Credentials: The Truth about Affirmative Action in Law Faculty Hiring. *Columbia Law Review* 97 No. 2: 199-311.

Meyers, L. S., G. Gamst, and A. J. Guarino. 2006. *Applied Multivariate Research: Design and Interpretation*. Thousand Oaks, CA: Sage Publications, Inc.

Miller, A. 2002. *Subset Selection in Regression*. 2nd ed. Boca Raton, FL: CRC Press LLC.

Morrison, E., E. Rudd, and M. Nerad. 2011. Onto, Up, Off the Academic Faculty Ladder: The Gendered Effects of Family on Career Transitions for a Cohort of Social Science Ph.D.s. *Review of Higher Education* 34 No. 4: 525–553.

Moss, S. A. 2006. Against "Academic Deference": How Recent Developments in Employment Discrimination Law Undercut an Already Dubious Doctrine. *Berkeley Journal of Employment and Labor Law* 27 No. 1: 1-22.

Munro, D. 1995. The Continuing Evolution of Affirmative Action under Title VII: New Directions after the Civil Rights Act of 1991. *Virginia Law Review* 81 No. 2: 565-610.

Murray, P. 1971. Economic and Educational Inequality Based on Sex: An Overview. *Valparaiso University Law Review* 5 No. 2: 237-280.

Nettles, M. T., L. W. Perna, E. M. Bradburn. 2000. *Salary, Promotion, and Tenure Status of Minority and Women Faculty in U.S. Colleges and Universities*. U. S. Department of Education, National Center for Education Statistics, National Study of Postsecondary Faculty, 1993 (NSOPF:93), http://nces.ed.gov/pubsearch/pubsinfo.asp?pubid=2000173 (accessed November 7, 2015).

Pacholski, S. L. 1992. Title VII in the University: The Difference Academic Freedom Makes. *University of Chicago Law Review* 59 No. 3: 1317-1336.

Paetzold, R. L. and S. L. Wilborn. 2012. *The Statistics of Discrimination: Using Statistical Evidence in Discrimination Cases*. 2012-2013 ed. Eagan, MN: Thomas Reuters.

Perna, L. W. 2001. Sex and Race Differences in Faculty Tenure and Promotion. *Research in Higher Education* 42 No. 5: 541-567.

Perna, L. W. 2005. Sex Differences in Faculty Tenure and Promotion: The Contribution of Family Ties. *Research in Higher Education* 46 No. 3: 277-307.

Perrucci, R., K. O'Flaherty, and H. Marshall. 1983. Market Conditions, Productivity, and Promotion among University Faculty. *Research in Higher Education* 19 No. 4: 431-449.

Peterson, D. W. 2003. Cohort Analysis: A Regression Plain and Fancy. *Journal of Forensic Economics* 16 No. 2: 153-176.

Piette, M. J. and J. R. Thornton. 1995. Cohort Analysis and the Determination of Economic Damages Resulting from Employment Discrimination. *Journal of Forensic Economics* 8 No. 1: 69-80.

Player, M. A. 2013. *Federal Law of Employment Discrimination in a Nutshell*. 7th ed. St. Paul, MN: West Academic Publishing.

Raymond, R. D., M. L. Sesnowitz, and D. R. Williams. 1993. Further Evidence on Gender and Academic Rank. *Quarterly Review of Economics and Finance* 33 No. 2: 197-215.

Roos, P. A. and M. L. Gatta. 2009. Gender (In)equity in the Academy: Subtle Mechanisms and the Production of Inequality. *Research in Social Stratification and Mobility* 27: 177-200.

Rosenfeld, R. A. and J. A. Jones. 1987. Patterns and Effects of Geographic Mobility for Academic Women and Men. *Journal of Higher Education* 58 No.5: 493–515.

Rothman, K. J., S. Greenland, and T. L. Lash. 2008. *Modern Epidemiology*. 3rd ed. Philadelphia, PA: Lippincott Williams and Wilkins.

Rothman, S., S. R. Lichter, and N. Nevitte. 2005. Politics and Professional Advancement among College Faculty. *Forum* 3 No. 1: Article 2.

Royston, P. and W. Sauerbrei. 2007. Improving the Robustness of Fractional Polynomial Models by Preliminary Covariate Transformation: A Pragmatic Approach. *Computational Statistics and Data Analysis* 51: 4240-4253.

Royston, P. and W. Sauerbrei. 2008. *Multivariable Model-Building: A Pragmatic Approach to Regression Analysis Based on Fractional Polynomials for Modelling Continuous Variables*. West Sussex, UK: John Wiley and Sons Ltd.

Rubin, K. 1981. Disparate Impact Suits under Title IX. *Stanford Law Review* 33 No. 4: 737-751.

Rudd, E., E. Morrison, R. Sadrozinski, M. Nerad, and J. Cerny. 2008. Equality and Illusion: Gender and Tenure in Art History Careers. *Journal of Marriage and Family* 70 No. 1: 228-238.

Sax, L. J., L. S. Hagedorn, M. Arredondo, and F. A. Dicrisi III. 2002. Faculty Research Productivity: Exploring the Role of Gender and Family-Related Factors. *Research in Higher Education* 43 No. 4: 423-446.

Schwartz, D. S. 2000. The Case of the Vanishing Protected Class: Reflections on Reverse Discrimination, Affirmative Action, and Racial Balancing. *Wisconsin Law Review* 2000 No. 3: 657-689.

Selvin, S. 2008. *Survival Analysis for Epidemiologic and Medical Research*. New York, NY: Cambridge University Press.

Shaw, A. K. and D. E. Stanton. 2012. Leaks in the Pipeline: Separating Demographic Inertia from Ongoing Gender Differences in Academia. *Proceedings of the Royal Society B* 279 No. 1743: 3736-3741.

Snell, C., J. Sorensen, J. J. Rodriguez, and A. Kuanliang. 2009. Gender Differences in Research Productivity among Criminal Justice and Criminology Scholars. *Journal of Criminal Justice* 17: 288-295.

Spector, P. E. 1981. *Research Designs*. Newbury Park, CA: Sage Publications, Inc.

Stack, S. 2004. Gender, Children and Research Productivity. *Research in Higher Education*. 45 No. 8: 891-920.

Szafran, R. F. 1983. A Note on the Recruitment and Reward Equity of Organizations: U.S. Universities before Affirmative Action. *Social Forces* 61 No. 4: 1109-1118.

Tableman, M. and J. S. Kim. 2004. *Survival Analysis Using S: Analysis of Time-to-Event Data*. Boca Raton, FL: Chapman and Hall/CRC.

Taylor, S. W., B. F. Fender, and K. G. Burke. 2006. Unraveling the Academic Productivity of Economists: The Opportunity Costs of Teaching and Service. *Southern Economic Journal* 72 No. 4: 846-859.

Toutkoushian, R. K. 1998. Sex Matters Less for Younger Faculty: Evidence of Disaggregate Pay Disparities from the 1988 and 1993 NCES Surveys. *Economics of Education Review* 17 No. 1: 55-71.

Turner, H. A. and C. C. Hetrick. 1972. Professions and the Ballot Box: A Comparison of Nine Academic Groups and the General Electorate. *Social Science Quarterly* 53 No. 3: 563-572.

Vittinghoff, E. and C. E. McCulloch. 2007. Relaxing the Rule of Ten Events per Variable in Logistic and Cox Regression. *American Journal of Epidemiology* 165 No. 6: 710-718.

West, M. S. 1994. Gender Bias in Academic Robes: The Law's Failure to Protect Women Faculty. *Temple Law Review* 67: 67-178.

Whalen, C. and B. Whalen. 1985. *The Longest Debate: A Legislative History of the 1964 Civil Rights Act*. Cabin John, MD: Seven Locks Press.

White, L. 2010. Fifty Years of Academic Freedom Jurisprudence. *Journal of College and University Law* 36: 791-842.

Winslow, S. 2010. Gender Inequality and Time Allocations among Academic Faculty. *Gender and Society* 24 No. 6: 769-793.

Wolf-Devine, C. 1993. Proportional Representation of Women and Minorities. In. *Affirmative Action and the University: A Philosophical Inquiry*, ed. S. M. Cahn. Philadelphia, PA: Temple University Press, 223-232.

Xie, Y. and K. A. Shauman. 1998. Sex Differences in Research Productivity: New Evidence about an Old Puzzle. *American Sociological Review* 63 No. 6: 847-870.

Zar, J. H. 2010. *Biostatistical Analysis*. 5th ed. Upper Saddle River, NJ: Pearson Prentice Hall.

Zelinsky, W. 1973. Women in Geography: A Brief Factual Account. *Professional Geographer* 25 No. 2: 151-165.

Zipp, J. F. and R. Fenwick. 2006. Is the Academy a Liberal Hegemony? The Political Orientations and Educational Values of Professors. *Public Opinion Quarterly* 70 No. 3: 304-326.