Essays on the STEM Trainee Labor Market

HARVARD UNIVERSITY
Graduate School of Arts and Sciences

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Essays on the STEM Trainee Labor Market

A dissertation presented

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Abstract

This dissertation consists of three essays on the careers of science, technology, engineering, and mathematics (STEM) Ph.Ds. The first essay constructs the career paths of 156,089 research doctorate holders over six job types and two employment statuses. Comparing STEM Ph.D. cohorts from 1950 to the present, postdoctoral positions have become increasingly prevalent despite the lengthening of doctoral training and reduced likelihood of obtaining an academic tenure-track position. I find evidence that postdoctoral positions allow STEM Ph.Ds. to persist in high-intensity academic research environments, albeit not necessarily on the tenure-track, at the cost of significant lifetime earnings. The second essay examines how constraints, such as dedicating time to childcare, may deter certain types of individuals from persisting in academia. I examine how a biological science Ph.D.'s first child's birth affects career trajectory and contributes to the academic tenure-track gender gap. Although there is no gender gap in tenure-track rates among individuals prior to the birth of their first child, mothers' reductions in work hours after having children lead to a 10 percentage point gender gap among tenure-track faculty. Because this child penalty is not observed in other job types such as industry and non-tenure track, I conclude that the long hours required by the tenure track's "up-or-out" structure deter mothers from these positions. Much work remains to fully examine the factors that affect STEM Ph.D. career trajectories and the frictions that deter underrepresented groups from academic research. The third chapter thus provides a guide to the available data resources for studying STEM Ph.D. careers. This white paper assists meta-researchers by detailing the application process, advantages, and shortcomings of current data collection. Examining the factors that affect STEM Ph.D. careers can inform policymakers on effective strategies for recruiting and retaining the research workforce.

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This thesis is dedicated to my parents.

Thank you for all you've done to get me to where I am today.

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1 What's Another Year?

The Lengthening Training and Career Paths of Scientists

1.1 Introduction

Over the past fifty years, the average time spent in graduate school for a science, technology, engineering, and mathematics (STEM) Ph.D. has increased by two years. At the same time, the probability of ever obtaining an academic tenure-track position has been nearly cut in half: compared to 43 percent of 1960-1980 graduating cohorts, only a quarter of STEM Ph.D. graduates today ever move into these positions. Despite the lengthening graduate training and the low probability of entering the tenure track, a growing 40 percent of STEM Ph.Ds. pursue postdoctoral positions. Postdoctoral positions do not improve one's chances at obtaining a tenure-track position: approximately 18 percent of STEM Ph.Ds. transition from their last postdoctoral appointment into tenure-track positions, compared to 22 percent of STEM Ph.Ds. who transition directly from graduate school. Rather, this paper finds evidence that postdoctoral positions allow STEM Ph.Ds. to remain in high-intensity academic research positions, albeit not necessarily on the tenure track: 79 percent of postdoctoral positions are at Carnegie-Classified very high research activity (R1) institutions, and postdoctoral researchers who remain in academia are approximately 20 percentage points more likely to transition to R1 universities than those transitioning directly from graduate school.[1]

However, these research opportunities come with a significant earnings loss: although postdoctoral researchers eventually transition into equal or higher salary jobs as their non-postdoctoral peers, each additional year is postdoctoral positions is associated with an approximately $3,700 deduction in undiscounted average of lifetime earnings.

The scientific community has long been concerned with the lengthening training of STEM Ph.Ds. for a shrinking number of academic tenure-track positions.(*Bridges to Independence: Fostering the Independence of New Investigators in Biomedical Research* 2005) However, limited research has focused on doctorate and post-doctorate stages of the STEM pipeline - especially outside of the biomedical fields.(Balsmeier and Pellens, 2014; Mathur, Cano, et al., 2018; Mishagina, 2009; Roach and Sauermann, 2016; *Science and Engineering Indicators* 2018; Stephan, 2012; Zolas et al., 2015)[2] This paper systematically examines the long-term trends of STEM Ph.D. career paths. Using the National Science Foundation (NSF)'s Survey of Earned Doctorates (SED) linked to the 1993-2015 longitudinal waves of the Survey of Doctorate Recipients (SDR), I create detailed career profiles for 156,089 research doctorate holders across ten STEM fields. Expanding

[1]The Carnegie Classification groups universities by the number of doctoral degrees conferred and amount of research funding utilized each year. A R1 "very high research activity" university (e.g. Harvard University, Stony Brook University) confers at least fifty doctoral degrees each year and has at least $40 million in federal research support.

[2]A larger literature has focused on STEM persistence at the pre-doctorate level (e.g. Blotnicky et al., 2018; Boudreau and Marx, 2019; Evans, 2017; Shu, 2015; Tai et al., 2006) or alternatively among established scientists (e.g. Azoulay, Ganguli, and Zivin, 2017; M. Levitt and J. Levitt, 2017). This is due to limited data particularly on postdoctoral researchers, which have historically been poorly tracked.(*Biomedical Workforce Working Group Report* 2012) There has only recently been a push for universities to collect the long-term career outcomes of their graduate students and postdoctoral researchers.(*Coalition of Next Generation Life Sciences* n.d.; Silva, Mejía, and Watkins, 2019)

Ginther and Kahn (2017)'s methodology for estimating postdoctoral incidence, I identify each post-Ph.D. year that an individual spends any portion of the year working in six job types - postdoctoral researcher, academic tenure-track, academic non-tenure track, for-profit industry, non-profit, and government - and in two employment statuses - unemployed and out of the labor force. I compare how these career paths and job characteristics change across 1950-2013 Ph.D. graduation cohorts.

I find that the average time spent in graduate programs between finishing the Bachelor's degree and completing the Ph.D. has increased from 5.8 years (s.d. = 2.1) among 1960-1980 STEM Ph.D. cohorts to 8.0 years (s.d. = 4.1) among 2000-2013 cohorts.[3] The probability of ever obtaining an academic tenure-track position has plummeted from 42.8% of 1960-1980 STEM Ph.Ds. to 25.2% of 2000-2013 cohorts. Despite this decline in probability, more STEM Ph.Ds. are pursuing postdoctoral positions each year: 40.2% of 2000-2013 cohorts are ever observed in postdoctoral positions, compared to 28.9% of 1960-1980 STEM Ph.Ds. The average STEM Ph.D. spends 2.7 years (s.d. = 2.3) in these postdoctoral positions. There is no evidence to suggest that this additional training improves a STEM Ph.D.'s chances at obtaining a tenure-track job: 18.4% of 2000-2013 cohorts with postdoctoral experience transition to tenure-track jobs after their last appointment, compared to 21.8% transitioning directly from their Ph.D. graduation.

Rather, the benefit of postdoctoral positions is that they provide a higher likelihood of remaining in high-intensity academic research, albeit not necessarily on the tenure track, than transitioning directly from graduate school. Consistent with the average STEM Ph.D.'s preference for academic research over industry positions established in the literature, I find evidence of a compensating differential for remaining in academia - particularly at research-intensive universities.(Agarwal and Ohyama, 2013; Conti and Visentin, 2015; Ganguli and Gaulé, 2018; Janger and Nowotny, 2016; Stern, 2004) Because of their temporary nature, postdoctoral positions allow flexibility in the transition to a permanent job sector. Non-postdoctoral positions are absorbing states: approximately 80 perceent of individuals who take on a permanent academic or for-profit industry job remain in the same job sector for the remainder of their career paths, compared to 13 percent of postdoctoral researchers. STEM Ph.Ds. who take on postdoctoral positions spend longer in high-intensity academic research than those who transition to permanent positions directly from their Ph.D. Among 2000-2013 STEM Ph.D. cohorts, 23.9% of STEM postdoctoral researchers transition to academic non-tenure track positions, compared to 8.7% of STEM Ph.Ds. directly from graduation. Postdoctoral researchers who remain in academia are approximately 20 percentage points more likely to transition from their last appointment to a Carnegie-Classified "very high research activity" university than Ph.Ds. who take on academic positions directly from graduate school.

[3] This measure combines time spent in both Master's and Doctorate degree programs, subtracting time out of school during this period.

Remaining in low-paying postdoctoral positions comes with a significant loss in lifetime earnings. Although postdoctoral researchers transition into positions with equal or higher starting salaries as those who transition directly from graduate school, this does not compensate for the lower postdoctoral wages early in their careers. Over a thirty year post-Ph.D. career, each additional postdoctoral year is associated with a $3,730 deduction in undiscounted average of lifetime earnings, rather than a typical education premium. From a salary perspective, the opportunity cost of pursuing postdoctoral experience is greater than the real market interest rate. This indicates that the non-pecuniary benefits of remaining in high-intensity academic research are likely a greater driver in the growth of individuals pursuing postdoctoral positions than skills investment.

Taken all together, postdoctoral appointments allow STEM Ph.Ds. to persist longer in high-intensity academic research, albeit not necessrily on the tenure track. As the number of postdoctoral researchers becomes more commonplace and the number of tenure-track positions declines, postdoctoral experience does not improve a STEM Ph.D.'s chances of obtaining a tenure-track position. Rather, postdoctoral researchers spend more time at very high research universities than those transitioning directly from graduate school. The temporary nature of postdoctoral appointments give STEM Ph.Ds. greater flexibility to transition into these high-intensity academic research positions over other permanent positions. However, this greater research opportunity comes at significant cost: low postdoctoral pay is not offset by higher earnings later in the career, leading to lower overall lifetime earnings compared to transitioning directly from graduate school. Thus, STEM Ph.Ds. considering postdoctoral positions must weigh the non-pecuniary costs of remaining in academic research with this earnings loss to determine if it is a worthwhile investment.

The remainder of this paper is organized as follows: Section 1.2 describes the NSF SED-SDR dataset and its advantages in constructing STEM Ph.D. career paths. Section 1.3 summarizes the construction of post-Ph.D. career paths and provides summary statistics. Section 1.4 presents trends across 1950-2013 Ph.D. cohorts and gives evidence of how postdoctoral positions provide opportunities for preferred high-intensity research activities at the cost of significant lifetime earnings. Section 1.5 discusses potential avenues for future research and concludes.

1.2 Data: NSF Survey of Earned Doctorates (SED) Linked to Survey of Doctorate Recipients (SDR)

This paper draws on the National Science Foundation (NSF)'s Survey of Earned Doctorates (SED) linked to the 1993-2015 waves of the NSF Survey of Doctorate Recipients (SDR). This is the largest, nationally representative sample of individuals receiving first-time research doctorates from accredited U.S. institutions in science, engineering, and health fields. Figure 1.1 gives the number of individuals in each Ph.D. graduation cohort that are represented by the SED-SDR data. The SED surveys individuals the year they apply for their Ph.D. graduation, then follows respondents on a roughly biennial basis in the SDR waves until they reach the age of 76, emigrate from the U.S.,[4] or are otherwise unable to respond.[5]

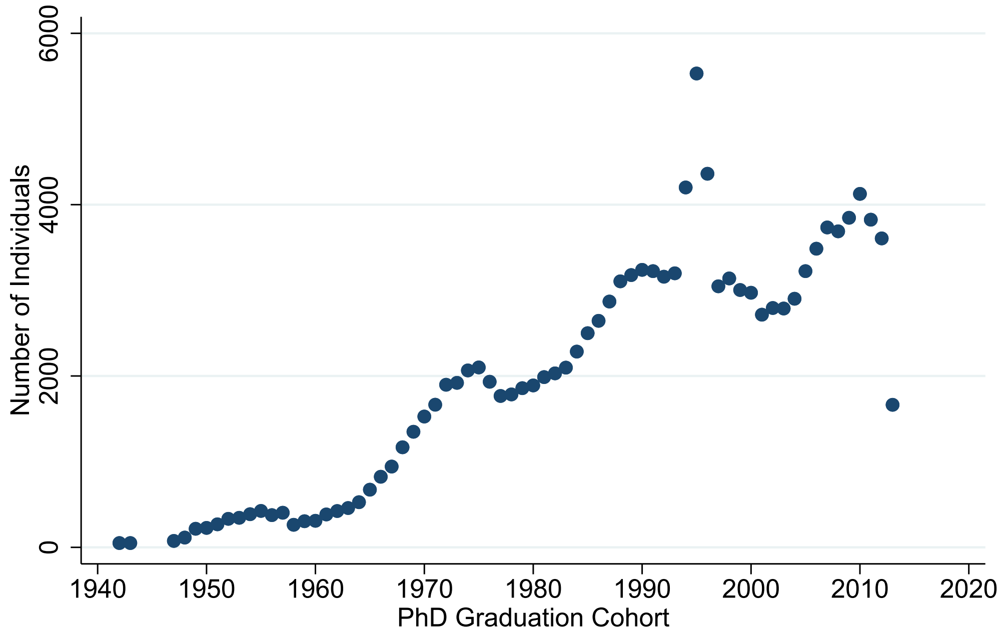


Figure 1.1: Number of Individuals in Each Ph.D. Graduation Cohort

Notes: This graph gives the number of individuals in each Ph.D. graduation cohort represented by the SED-SDR data. For disclosure purposes, only cohorts with at least fifty individuals are shown.

Each survey collects extensive information on the doctoral recipient's individual demographics, education, and job characteristics. From the SED, respondents provide information on their education through the doctorate and their immediate post-graduation plans. In each following SDR wave, respondents answer a wide range of questions about their current job such as their employment sector, most common work activities, and annual salary. Some questions also shed light on work experience in between surveys such as their current job's starting date and whether one has changed jobs since the last survey. Based on these responses, the SED-SDR paints a detailed picture of an individual's career over time.

[4]Starting in 2010, the survey expanded to include U.S. research doctorate earners residing outside of the U.S. through the International SDR (ISDR). However, given limited data on expats, this project focuses on individuals who obtained their Ph.Ds. in the U.S. and remain in the U.S.

[5]This consists of individuals who are known to be deceased, terminally ill, incapacitated, or permanently institutionalized in a correctional or health care facility.

One limitation of the SED-SDR is that the survey has limited information on ability proxies. A few survey waves (1995, 2001, 2003, and 2008) ask respondents about their five-year publication and patent rates; this question has since been discontinued. No question asks about cumulative number of publications or number of patents. Thus, I am limited to information at the academic institution level for an individual respondent's ability proxy. In particular, I use the Carnegie Classifications provided by the SED-SDR as a measure of educational prestige. Since 1970, the Carnegie Classification groups U.S. universities by the yearly number and types of degrees conferred and the amount of research expenditures as reported through the NSF Higher Education Research & Development (HERD) Survey.(*The Carnegie Classification of Institutions of Higher Education* n.d.)[6] These classifications are updated approximately every five years. The SED-SDR data provides Carnegie Classifications for the academic institutions from which an individual receives their Bachelor's, Master's, and Doctorate degrees. If an individual works at an academic institution after their Ph.D. graduation, I further merge on the institution's Carnegie Classification at the time of employment.

Overall, the response rate for a SDR wave is approximately 70 percent.(Foley, 2015) Individuals who do not respond to a specific SDR wave remain in the sample and continue to be contacted for future waves until they are no longer eligible (as defined by the conditions in Footnote 5). Thus, it is possible for individuals to miss multiple waves but respond later. For the 1993-2015 SDR waves, Table 1.1 gives a comparison between the number of waves an individual is expected to have responded to the SDR - based on their Ph.D. graduation year and age - to the actual number of waves an individual is observed in the SDR. The fewer waves contributed to the SDR, the less complete of a career path can be constructed.

[6] This paper focuses on the doctoral university classifications: "R1 - very high research" awards at least fifty doctoral degrees per year and have at least \$40 million in federal research support (e.g. Harvard University, Stony Brook University); "R2 - high research" awards at least fifty doctoral degrees per year and have between \$15.5 - \$40 million in federal research support (e.g. American University, Eastern Michigan University); "D1 - doctoral I" awards at least fifty doctoral degrees per year and has less than \$15.5 million in federal research support (e.g. Drake University, Indiana State University); and "D2 - doctoral II" awards between ten to forty doctoral degrees per year (discontinued from classification system in 2000; e.g. Loma Linda University, University of Alabama in Huntsville).

Table 1.1: Comparison of Number of Waves Expected in SDR vs. Actually in SDR

		Expected Waves										
		1	2	3	4	5	6	7	8	9	10	11
Actual Waves	0	31.8%	1.8%	5.6%	6.4%	6.6%	6.8%	6.4%	7.3%	12.8%	18.0%	7.6%
	1	68.2%	95.6%	79.3%	61.3%	57.9%	52.3%	49.1%	46.8%	42.4%	44.5%	42.7%
	2		2.7%	12.0%	18.0%	8.1%	7.3%	7.2%	6.2%	6.6%	6.9%	7.8%
	3			3.1%	11.4%	12.6%	8.7%	7.3%	7.7%	6.3%	4.9%	10.1%
	4				2.9%	11.0%	12.0%	6.5%	5.2%	4.9%	2.9%	3.9%
	5					3.8%	8.9%	11.0%	5.5%	4.0%	3.4%	3.2%
	6						4.1%	8.1%	9.8%	4.3%	2.8%	2.5%
	7							4.4%	8.2%	8.1%	3.3%	3.3%
	8								3.4%	6.4%	5.8%	2.7%
	9									4.3%	4.1%	4.4%
	10										3.4%	8.4%
	11											3.3%
Total		534	10,794	9,601	9,097	11,870	7,803	7,832	8,246	10,597	12,764	66,716

Notes: This table compares a SDR individual's expected number of survey waves - defined as the number of surveys in which the SDR individual has graduated from their Ph.D. but less than 76 years after their given birth year - to the actual number of survey waves the individual is observed. Due to missing birth years, it is possible for individuals to be observed in more years than expected; however, those numbers are small and have been suppressed for disclosure purposes. Each cell of column m and row n gives the percentage of individuals expected in m waves that are observed n times. Perfect response rate would be a 100% on the diagonal. The final row gives the total number of individuals expected in m waves.

1.3 Methodology: Tracking STEM Ph.D. Careers

For all individuals in the 1993-2015 SDR waves, I construct career paths that measure their experience in six job types - postdoctoral researcher, academic tenure-track, academic non-tenure track, for-profit industry, non-profit, and government - and two employment statuses - unemployed and not in the labor force. This construction is an expansion of Ginther and Kahn (2017)'s measurement of postdoctoral incidence: using the vast SED-SDR data, I identify each post-Ph.D. year in which a respondent spends any portion of the year working in the job type or employment status of interest. Appendix A.1 details this career path construction and gives a hypothetical example using this methodology. Figure 1.2 gives the number of jobs that are identified by this methodology in each year post-Ph.D. graduation for each decade of graduation cohorts.

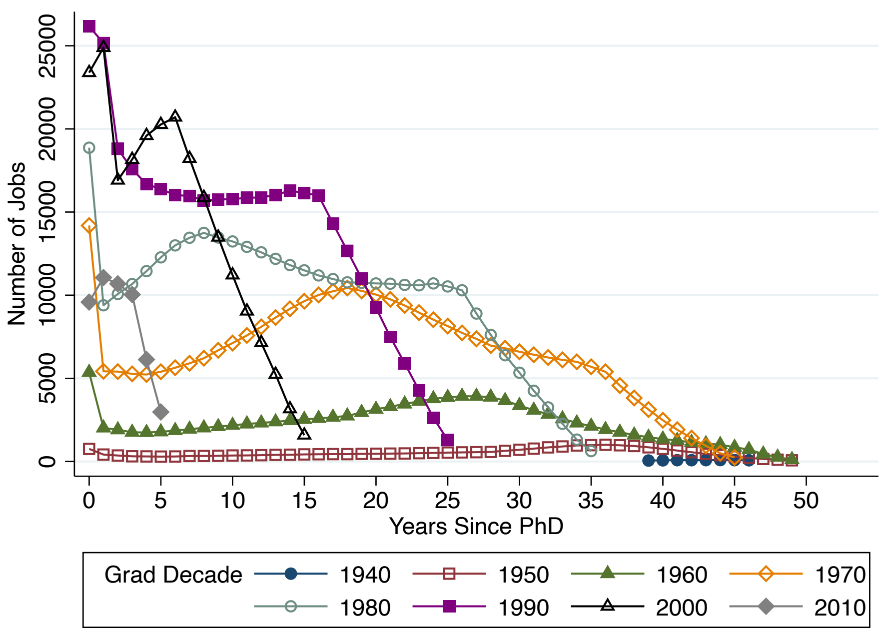


Figure 1.2: Number of Jobs Represented in Each Year Since Ph.D. Graduation

Notes: This graph gives the number of jobs identified in each year since Ph.D. graduation, grouping individuals by the decade during which they graduated. For disclosure purposes, only groups representing at least fifty jobs are shown.

There are considerable gaps in the data: 35.1% of individual-year cells do not have any employment information. This is to be expected, given that 68.3% of the sample graduated from their Ph.Ds. at least two years before the first available SDR wave in 1993 - thereby missing some portion of their career path - and the level of non-response to eligible SDR waves given in Table 1.1.

I perform limited interpolation on worker and job characteristics across non-survey years, as described in Appendix A.2. To examine the impact of postdoctoral experience on career earnings, I modify Bhuller, Mogstad, and Salvanes (2017)'s schooling regression to analyze thirty-year post-Ph.D. salary paths:

$$Y_a = \alpha_a + \beta_a P + \epsilon_a \tag{1.1}$$

where in each year post-Ph.D. graduation a, Y_a gives annual real salary (in 2015 dollars) and P gives years of postdoctoral experience. I include fixed effects for Ph.D. field of study, graduation year, and current job type. I then use the yearly postdoctoral coefficient estimates to compute the postdoctoral premium (or deduction) in undiscounted average of thirty-year post-Ph.D. lifetime earnings:

$$\bar{\beta} = \sum_{a=0}^{30} \frac{\beta_a}{30} \tag{1.2}$$

The full career paths dataset consists of 156,089 individuals holding 300,944 unique jobs. Limiting the sample to ten STEM fields of study gives 135,599 individuals holding 258,873 unique jobs. Table 1.2 gives the distribution of fields for the full sample and the STEM sample.

Table 1.2: Weighted Percentage of SDR Individuals Receiving First Doctorate in General Field of Study

Ph.D. General Field of Study	*Full SDR Sample* (1)	*STEM Sample* (2)
Agricultural Sciences/Natural Resources	4.2%	4.9%
Biological/Biomedical Sciences	20.5%	23.9%
Chemistry	9.1%	10.6%
Computer & Information Sciences	2.5%	2.9%
Economics	2.9%	-
Education	0.7%	-
Engineering	18.9%	22.0%
Health Sciences	4.4%	5.1%
Humanities	0.6%	-
Mathematics	4.4%	5.1%
Physics	5.4%	6.3%
Professional Fields	0.1%	-
Psychology	13.1%	15.4%
Other Physical Sciences	3.3%	3.9%
Other Social Sciences	9.7%	-

Notes: This table gives the weighted percentage of SDR individuals that received their first doctorate in each general field of study. Column 1 gives the full sample of 1993-2015 SDR individuals; Column 2 limits the sample to individuals in STEM fields.

For analysis, I focus on four major STEM fields of study: biological sciences, chemistry, engineering, and physics.[7] Table 1.3 gives summary statistics on Ph.D. demographics. Table 1.4 gives summary statistics on experience in each job type and employment sector. Table 1.5 gives summary statistics on job characteristics.

[7]Figures in the main text give results for biological sciences, the largest STEM field. Appendix B gives figures for chemistry, engineering, and physics.

Table 1.3: Ph.D. Individual Characteristics

	STEM (1)	Bio Sciences (2)	Chemistry (3)	Engineering (4)	Physics (5)
Male	69.9%	61.6%	77.3%	87.1%	89.4%
Race					
White	64.9%	68.7%	64.1%	47.2%	64.5%
Asian	25.4%	22.3%	27.1%	44.0%	28.6%
Underrepresented Minority	7.1%	6.6%	5.9%	6.4%	3.9%
At Ph.D. Graduation					
Age	32.0 (5.6)	31.5 (4.6)	29.9 (4.0)	31.6 (4.8)	30.5 (3.9)
Married	61.0%	59.5%	59.7%	63.1%	58.8%
Have Children	41.6%	37.3%	40.4%	45.3%	40.6%
US Native	65.8%	71.8%	68.3%	43.3%	61.1%
US Naturalized	4.0%	4.4%	3.1%	4.7%	3.6%
Ever Married	85.5%	84.5%	87.0%	88.9%	85.5%
Ever Have Children	63.4%	61.7%	62.8%	67.7%	61.9%
Research-Intensive					
Bachelor's	51.2%	50.8%	39.4%	65.9%	55.4%
Master's	68.4%	63.9%	67.4%	79.5%	78.5%
Doctorate	78.5%	78.9%	82.8%	84.3%	84.7%
Have Professional Degree	1.6%	4.4%	0.2%	0.2%	0.2%
Years in Graduate School	7.1 (3.2)	7.0 (2.7)	6.1 (2.3)	6.9 (3.0)	6.9 (2.5)
Total Number of Individuals	135,599	34,281	11,558	28,283	8,348

Notes: This table gives individual demographics - gender, race, age (standard deviation in parentheses), marital status, parental status, U.S. citizenship status, educational prestige as measured by the Carnegie Classification system, indicator for having a professional degree (e.g. M.D., J.D., M.B.A.) by Ph.D. graduation, and years in graduate school (standard deviation in parentheses) - for all STEM (column 1), bio sciences (column 2), chemistry (column 3), engineering (column 4), and physics (column 5) Ph.Ds.

Table 1.4: Ph.D. Experience in Job Types and Employment Sectors

	STEM (1)	Bio Sciences (2)	Chemistry (3)	Engineering (4)	Physics (5)
A. Percent Ever in Position					
Postdoc	37.0%	60.9%	45.9%	20.8%	48.2%
Tenure-Track	32.8%	32.7%	23.1%	25.6%	28.8%
Non-Tenure Track	17.7%	22.0%	14.0%	11.2%	17.7%
Industry	43.6%	30.1%	56.2%	62.1%	43.5%
Government	14.8%	13.8%	11.5%	12.5%	18.6%
Non-Profit	11.4%	12.5%	7.5%	8.3%	10.6%
Unemployed	3.6%	3.8%	5.5%	3.5%	4.1%
Not in Labor Market	14.9%	14.2%	21.7%	12.4%	17.4%
B. Average Conditional Years					
Postdoc	2.8 (2.5)	3.1 (2.6)	2.5 (2.2)	2.3 (2.0)	2.8 (2.4)
Tenure-Track	12.0 (11.2)	12.4 (10.8)	14.4 (12.4)	12.2 (11.3)	13.8 (12.1)
Non-Tenure Track	8.0 (7.4)	7.5 (7.0)	8.0 (7.7)	7.7 (7.5)	8.7 (8.4)
Industry	10.5 (8.8)	8.9 (7.8)	11.4 (9.3)	9.7 (8.5)	10.8 (9.2)
Government	8.1 (9.2)	8.3 (8.4)	8.5 (9.5)	7.5 (8.5)	9.2 (10.3)
Non-Profit	6.4 (7.5)	6.2 (6.5)	6.5 (8.2)	5.4 (7.7)	8.5 (9.9)
Unemployed	3.3 (2.6)	3.1 (2.3)	3.5 (2.8)	3.3 (2.6)	3.4 (2.6)
Not in Labor Market	7.6 (5.6)	7.2 (5.5)	8.7 (6.0)	7.8 (5.4)	7.7 (5.7)
Total Number of Individuals	135,599	34,281	11,558	28,283	8,348

Notes: Panel A of this table gives the percent of all STEM (column 1), biological sciences (column 2), chemistry (column 3), engineering (column 4), and physics (column 5) Ph.Ds. who ever hold a certain job type (postdoctoral researcher, tenure-track, non-tenure track, for-profit industry) or employment status (unemployed, not in labor force). Conditional on any experience in a certain job type or employment status, Panel B of this table gives the average number of years spent in these positions (standard deviations in parentheses).

Table 1.5: Job Characteristics Held by Ph.Ds.

	STEM	Bio Sciences	Chemistry	Engineering	Physics
	(1)	(2)	(3)	(4)	(5)
Job Tenure	5.9 (7.3)	5.3 (6.6)	5.9 (7.3)	5.9 (6.9)	6.2 (7.7)
Salary (2015 Dollars)	$105,737 ($70,640)	$100,801 ($77,643)	$110,042 ($70,105)	$121,365 ($72,254)	$112,497 ($67,799)
Benefits					
Health Insurance	87.9%	90.7%	90.4%	91.5%	90.2%
Pension	80.5%	80.2%	81.6%	82.5%	82.9%
Profit Sharing	20.9%	15.7%	28.4%	32.6%	22.2%
Vacation Time	81.8%	85.6%	84.8%	86.6%	85.0%
Hours Worked	45.9 (12.5)	48.6 (12.8)	46.5 (12.1)	46.3 (11.3)	46.1 (11.9)
Full Time ($\geq$35 Hours)	90.1%	92.8%	92.3%	93.5%	92.2%
Most Frequent Work Activity					
Applied Research	16.9%	24.0%	18.6%	12.5%	19.2%
Basic Research	18.1%	23.1%	18.0%	17.0%	17.3%
Management	13.2%	12.2%	15.2%	15.4%	11.9%
Teaching	18.4%	16.4%	17.1%	12.7%	16.3%
Total Number of Unique Jobs	258,873	69,770	24,028	50,206	16,355

Notes: This table gives select job characteristics - average time spent, salary (adjusted for inflation to 2015 dollars; standard deviation in parentheses), benefits, weekly hours (standard deviation in parentheses), and select work activities on which spend most time - for all STEM (column 1), biological sciences (column 2), chemistry (column 3), engineering (column 4), and physics (column 5) Ph.Ds.

1.4 Results

1.4.1 Training Time Steadily Increasing

Over the past fifty years, mean time spent in graduate school has steadily increased by 2.2 years, from 5.8 years (s.d. = 2.1) among 1960-1980 STEM Ph.Ds. to 8.0 years (s.d. = 4.1) among 2000-2013 cohorts. For example, Figure 1.3 shows that time in biological science graduate school began a steady increase in the 1970's and has only recently stabilized.[8]

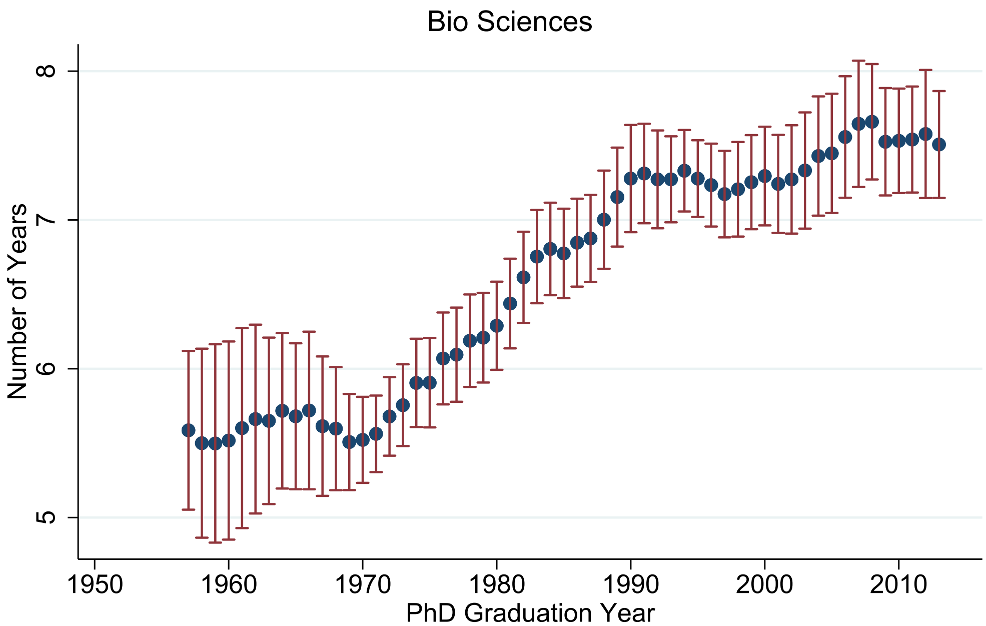


Figure 1.3: Mean Years in Graduate School by Ph.D. Cohort

Notes: This graph gives the three-year moving 95% confidence intervals for the mean years biological sciences Ph.Ds. spend in graduate school, defined as Ph.D. graduation year minus Bachelor's graduation year and time spent out of school during these years, for each Ph.D. graduation cohort. For disclosure purposes, only cohorts with at least fifty individuals are shown.

This increase is not explained by individuals taking more time off between undergraduate and graduate school. Figure 1.4 demonstrates time out has remained relatively low over time: the average STEM trainee spends approximately 1.3 years (s.d. = 2.7) between their Bachelor's and their Ph.D. not in school. This increase is due to a shift rather than widening of the distribution: Figure 1.5 demonstrates that fewer individuals are completing Ph.Ds. in fewer than four years and more individuals are completing Ph.Ds. in more than eight years over time.

[8]Similar increases are observed in chemistry, engineering, and physics. (See Appendix Figure B.1.)

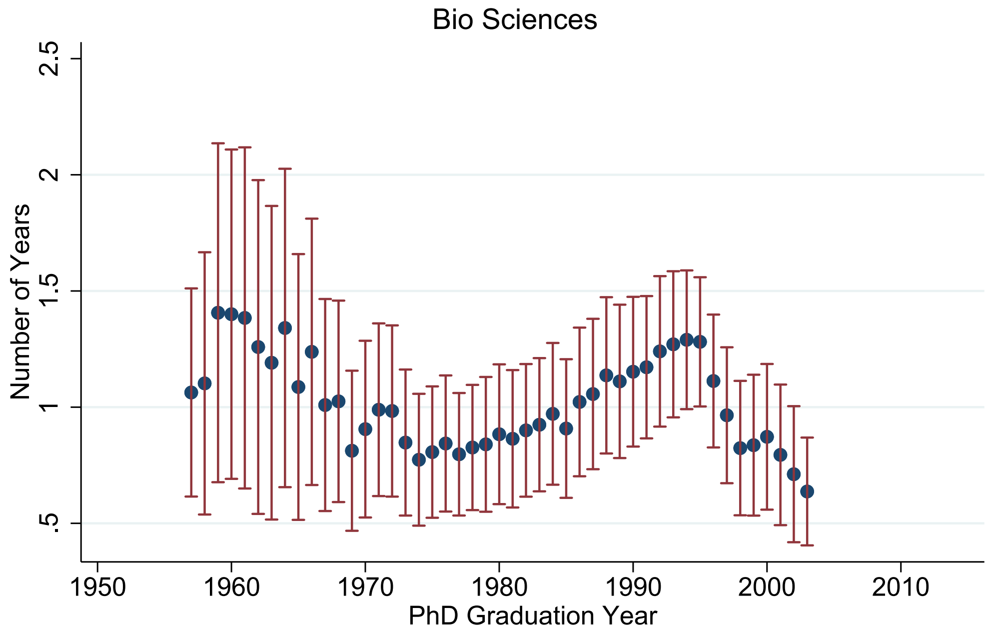


Figure 1.4: Mean Time Out of Graduate School by Ph.D. Cohort

Notes: This graph gives the three-year moving 95% confidence intervals for the mean time out between Bachelor's and Ph.D. graduation years for biological science Ph.Ds. For disclosure purposes, only cohorts with at least fifty individuals are shown.

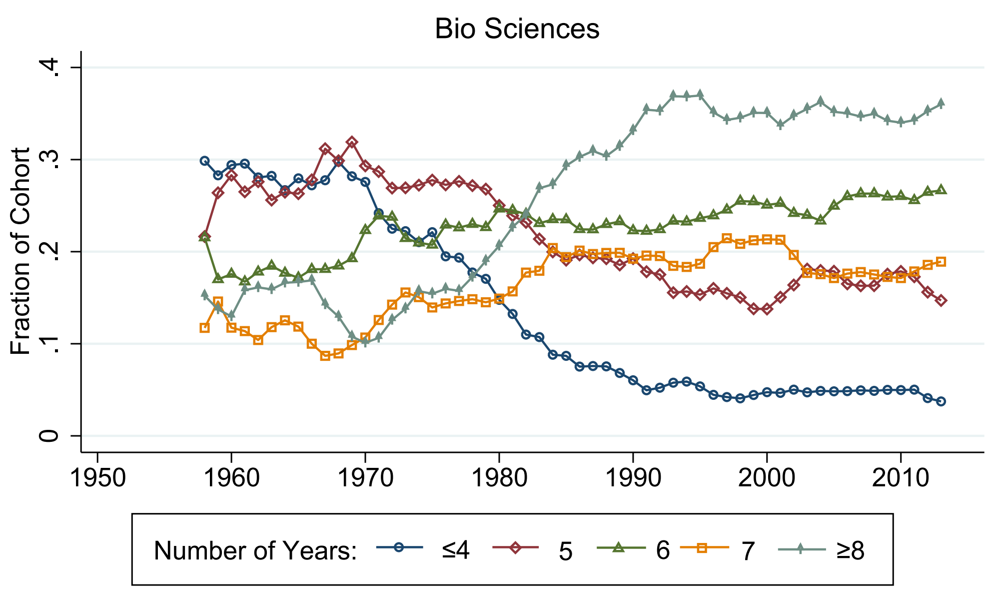


Figure 1.5: Distribution of Years in Graduate School by Ph.D. Cohort

Notes: This graph gives the three-year moving distribution of biological science Ph.Ds.' years spent in graduate school, defined as the time between the Bachelor's and Ph.D. graduation year minus the number of years spent out of school during this time. Years are rounded down to the nearest integer. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown; some years are combined or suppressed due to low counts.

Despite the lengthening of time in graduate school, the percent of STEM PhD graduates pursuing post-doctoral appointsment grew from 28.9% of 1960-1980 graduating cohorts to 40.2% of 2000-2013 cohorts. This trend is especially prevalent in the biological sciences: Figure 1.6 illustrates that over 60 percent of 2000-2013 biological science Ph.D. graduates transition directly to postdoctoral positions, compared to only 20 percent of 1950's cohorts.[9]

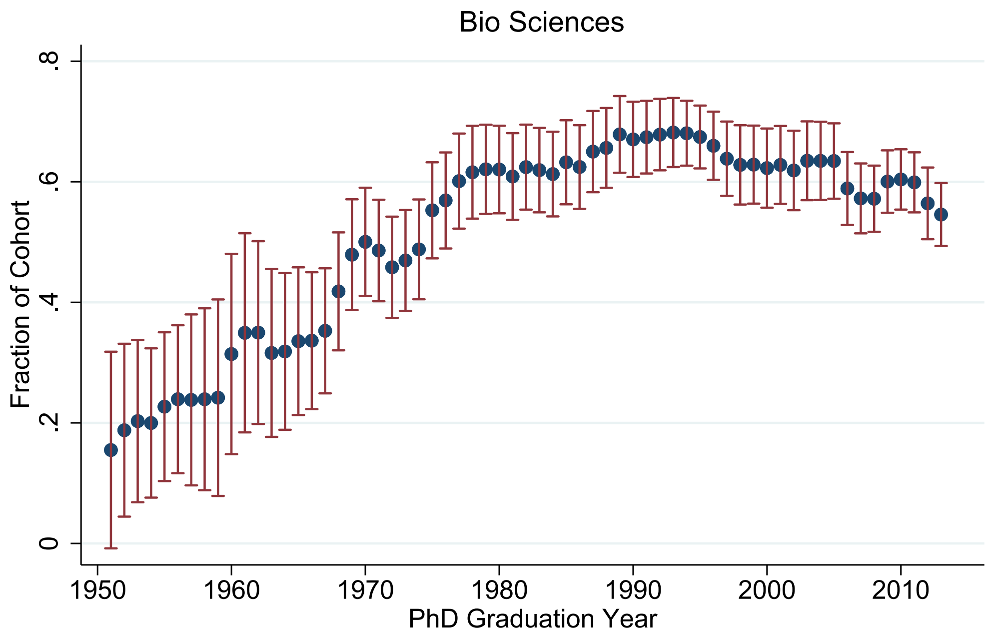


Figure 1.6: Early Postdoctoral Takeup by Ph.D. Cohort

Notes: This graph gives the three-year moving 95% confidence intervals for the fraction of each biological science Ph.D. cohort that take on postdoctoral positions within two years of graduation. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown.

Time spent in postdoctoral positions has not varied significantly in this time period despite more individuals pursuing these positions. Conditional on any postdoctoral experience, the average time spent in postdoctoral positions across all STEM fields since 1970 is 2.7 years (s.d. = 2.3). As shown in Figure 1.7, the distribution of postdoctoral years among biological sciences Ph.Ds. with any postdoctoral experience is relatively stable over time. This suggests that the purpose of postdoctoral positions has not significantly changed over time. Unlike the concurrent lengthening of graduate school, which arguably stems from requiring more time to build up a base of scientific knowledge, the rapid expansion of scientific literature in the last fifty years has not led to longer specialized training at the postdoctoral level. All together, between graduate and postdoctoral training, STEM Ph.Ds. now spend on average 9.1 years in specialized training

[9] A near majority of chemistry and physics Ph.Ds. have also transitioned directly to postdoctoral positions since the 1980's. Engineering, which had almost no Ph.Ds. transition directly to postdoctoral positions in the 1960's, has also increased to approximately 20 percent of chorts moving into postdoctoral positions. (See Appendix Figure B.4.)

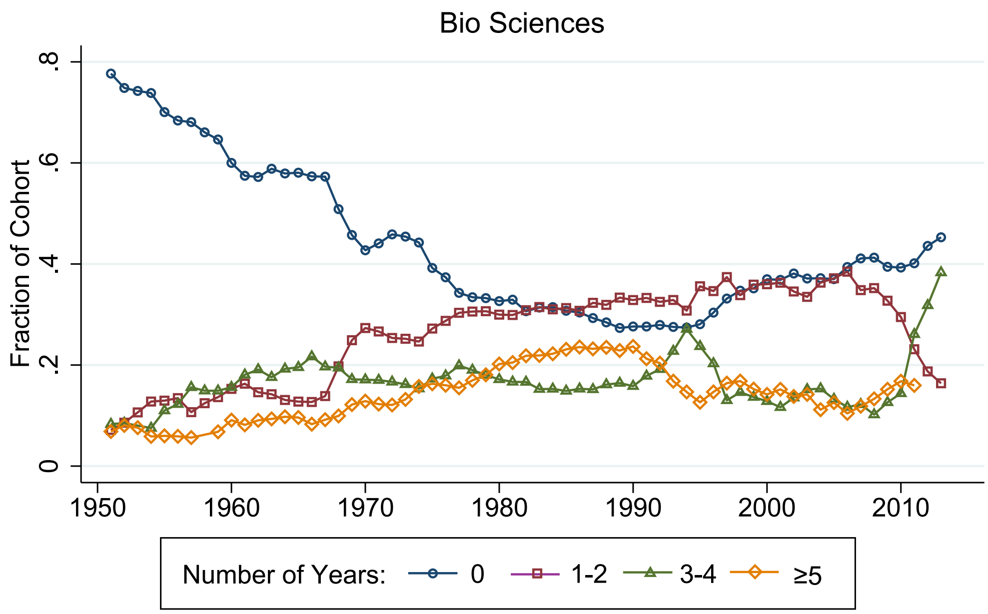


Figure 1.7: Distribution of Postdoctoral Years by Ph.D. Cohort

Notes: This graph gives the three-year moving distribution of biological science Ph.Ds.' years observed in postdoctoral positions for each Ph.D. cohort. Half-years spent in postdoctoral positions are rounded down. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown; some years are combined or suppressed due to low counts.

before their first permanent position.

1.4.2 Trainees No Longer Transition to Tenure-Track But to Other Jobs

As doctoral training has lengthened and more STEM Ph.Ds. have pursued postdoctoral training, the probability of obtaining an academic tenure-track position has nearly halved over the past fifty years. Only 25.2% of 2000-2013 STEM Ph.D. graduating cohorts are ever observed in a tenure-track position, compared to 42.8% of 1960-1980 cohorts. As shown in Figure 1.8, after the post-World War II boom in scientific research during the 1950's, the percent ever observed in tenure-track positions has steadily declined since the mid-1960's.(Bush, 1945)[10] Despite the focus of doctoral programs on academic tenure-track careers, only 21.8% of 2000-2013 STEM Ph.D. cohorts transition into these positions directly from graduate school.(Anderson, 2019; Loriaux, 2019)

[10]Similar declines are observed in engineering and physics. Chemistry, which had the lowest tenure-track rates in the 1960's, experienced a small drop before stabilizing at approximately 20 percent since the 1980's. (See Appendix Figure B.6.)

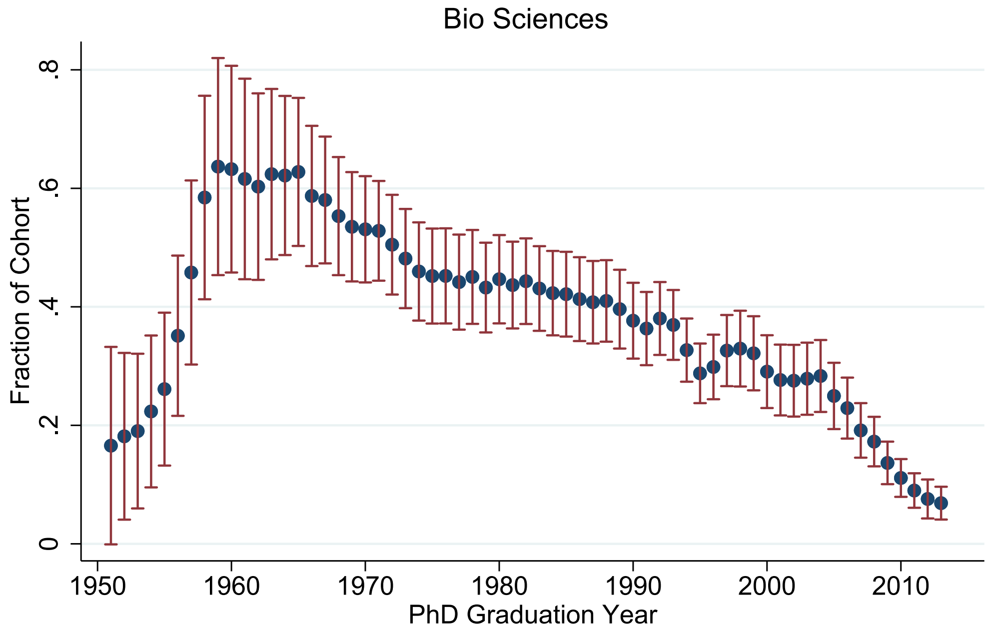


Figure 1.8: Percent Ever Observed in an Academic Tenure-Track Position by Ph.D. Cohort

Notes: This graph gives the three-year moving 95% confidence intervals for the percent of each biological science Ph.D. cohort that is ever observed in an academic tenure-track position. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown.

Historically, postdoctoral experience improved one's competitiveness in obtaining a tenure-track position: 40.9% of 1960-1980 STEM Ph.D. cohorts with postdoctoral experience transitioned to tenure-track positions, compared to 37.2% of those graduating in the same years with no postdoctoral experience. However, comparing Figures 1.9 and 1.10, 2000-2013 graduating Ph.Ds. with postdoctoral experience are not significantly more likely to obtain tenure-track positions as those without postdoctoral experience.[11] Only 18.4% of STEM postdoctoral researchers who graduated between 2000-2013 transition to tenure-track jobs. Thus, there is no evidence to suggest that postdoctoral experience improves one's job prospects on the academic tenure track.

[11]Chemistry and engineering, which have seen less drastic increases in the percent of graduate students pursuing postdoctoral appointments, have been relatively consistent in the percent of postdoctoral researchers transitioning to tenure-track. These percents are also similar to that of individuals transitioning directly from graduate school. (See Appendix Figures B.7 and B.8.)

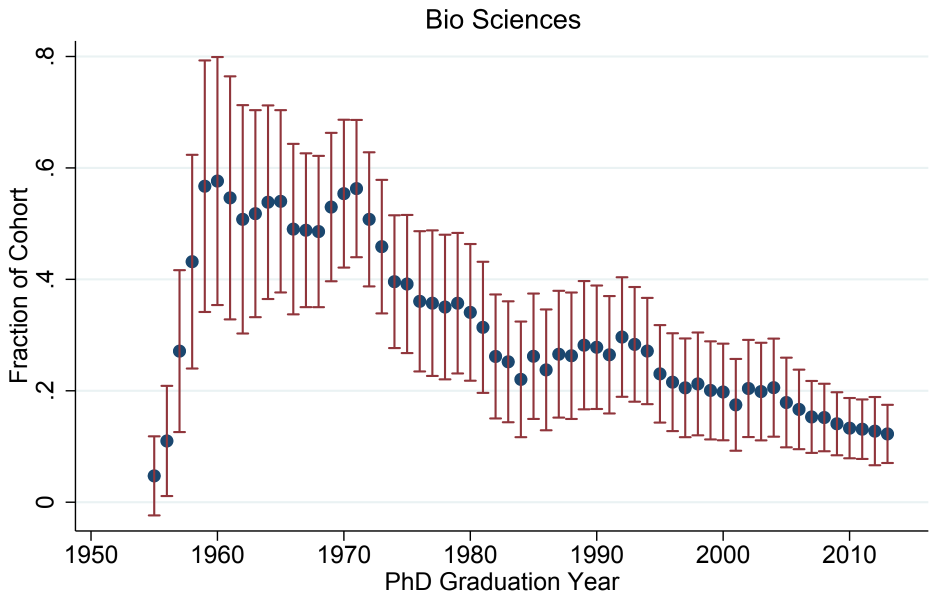


Figure 1.9: Fraction Observed in an Academic Tenure-Track Position with No Postdoctoral Experience by Ph.D. Cohort

Notes: This graph gives the three-year moving 95% confidence intervals for the fraction of each biological science Ph.D. cohort observed in an academic tenure-track position within two years of their Ph.D. graduation without any postdoctoral experience. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown.

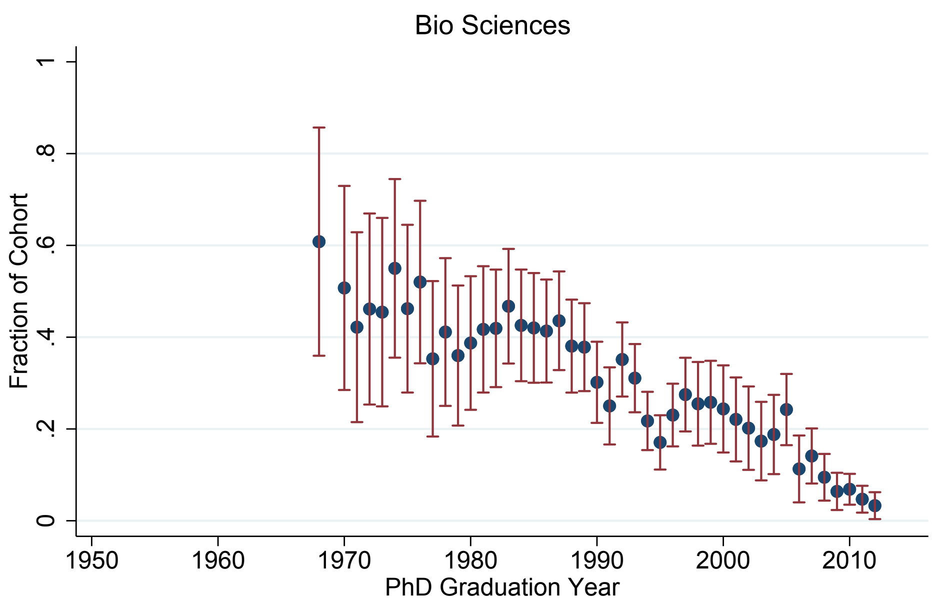


Figure 1.10: Fraction Transition from Postdoctoral Position to an Academic Tenure-Track Position by Ph.D. Cohort

Notes: This graph gives the three-year moving 95% confidence intervals for the percent of postdoctoral researchers from each biological science Ph.D. cohort who transition to a tenure-track, academic position within two years of their last postdoctoral position. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown.

It is now more likely that STEM Ph.Ds. work in job sectors outside of tenure-track academia. Among individuals identified in job types ten years after their Ph.D. graduation, Figure 1.11 gives the fraction of each graduation cohort that are in each job type. Although 47.5% of 1960-1980 STEM Ph.Ds. were in tenure-track academic positions ten years after their Ph.D. graduation, 2000-2013 cohorts are almost evenly distributed across tenure-track (28.1%), industry (36.0%), non-tenure track (16.6%), and government or non-profits (15.7%).

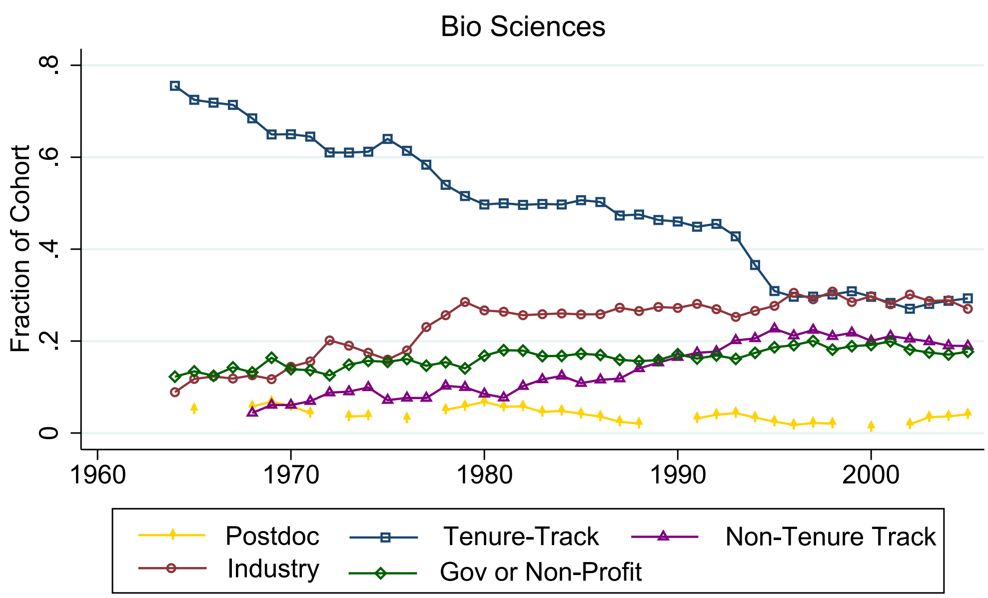


Figure 1.11: Job Distributions Ten Years Post-Ph.D. Graduation

Notes: This graph gives the three-year moving fraction of each biological science Ph.D. cohort working ten years post-Ph.D. graduation in each job type. Individuals who are not working or do not have data ten years post-Ph.D. are not included. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown.

Moving away from the tenure track and into "alternative" job sectors occurs for both individuals transitioning directly from graduate school and those who transition from postdoctoral appointments. Figure 1.12 gives the distribution of job types within two years of Ph.D. graduation for biological science Ph.Ds. with no postdoctoral experience. Figure 1.13 gives the distribution of job types that postdoctoral researchers take within two years of their last appointment. A growing percentage of STEM Ph.Ds. take for-profit industry jobs: compared to 17.9% of 1960-1980 cohorts, 22.8% of 2000-2013 cohorts transition to industry directly from graduate school.[12] Especially among postdoctoral researchers, academic non-tenure track positions have become increasingly popular. Among 2000-2013 STEM Ph.D. cohorts, 8.7% of new graduates and

[12]Engineering, which already had a considerable percent of Ph.D. graduates transition directly to industry between 1960-1980, has also seen the percent transitioning to industry widen over time. (See Appendix Figure B.10.)

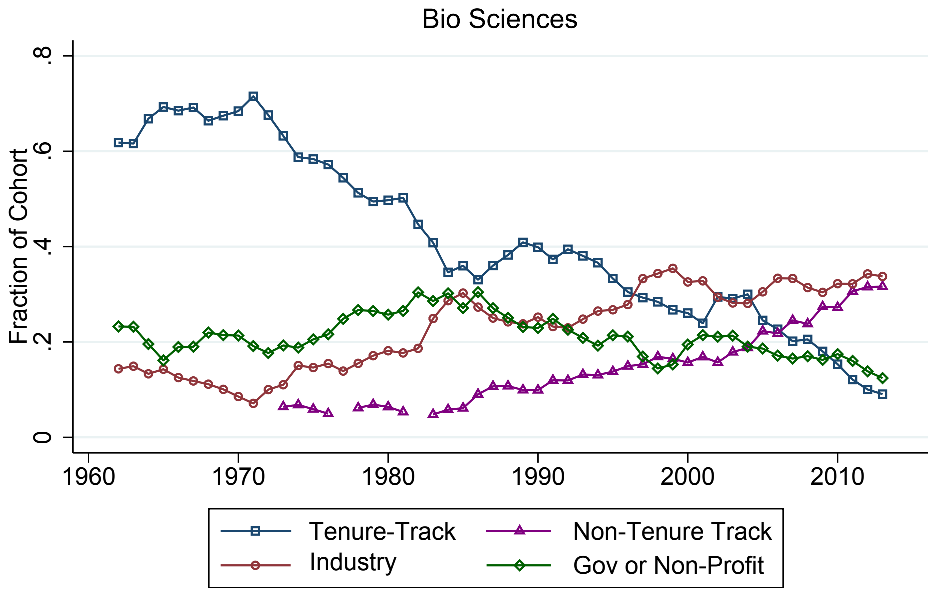


Figure 1.12: Distribution of Non-Postdoc Job Transitions After Ph.D. Graduation by Ph.D. Cohort

Notes: This graph gives the three-year moving fraction of each biological science Ph.D. cohort who do not have postdoctoral experience that transition into each non-postdoc job type within two years of their graduation. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown; some job types are combined or suppressed due to low counts.

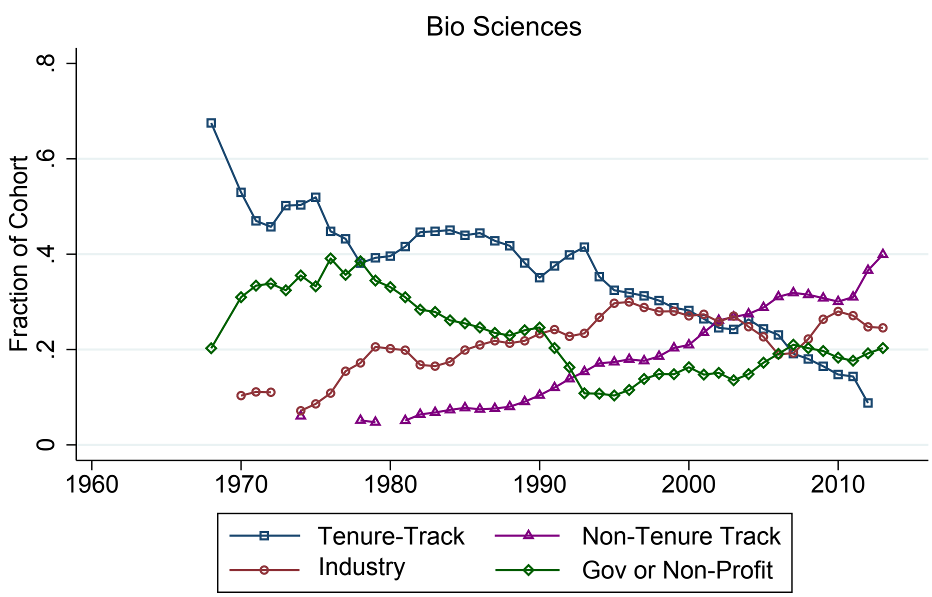


Figure 1.13: Distribution of Job Transitions After Last Postdoctoral Appointment by Ph.D. Cohort

Notes: This graph gives the three-year moving fraction of each biological science Ph.D. cohort who have postdoctoral experience that transition into each non-postdoctoral job types within two years of their last postdoctoral position. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown; some job types are combined or suppressed due to low counts.

23.9% of postdoctoral researchers transitioned into non-tenure track jobs.[13]

1.4.3 Postdocs as Opportunity for High-Intensity Academic Research

As a larger percent of postdoctoral researchers transition to academic non-tenure track jobs than new Ph.D. graduates, this may indicate that individuals with a higher preference for academic jobs - regardless of tenure status - are selecting into postdoctoral positions. Previous literature has documented researchers' willingness to trade off salary for greater research time.[14] Consistent with these results, many STEM Ph.Ds. pursue academic positions - postdoctoral researcher, tenure-track, and non-tenure track - that have high research activities but low salaries compared to industry positions. Figure 1.14 gives the fraction of respondents holding each job type that state they spend the most hours on select work activities, and Figure 1.15 gives the average salary for each job type. STEM industry jobs have the least focus on research - with 2.3% spending the most time on basic research - but have the highest average salary at $127,469. Comparatively, 21.8% of tenure-track positions and 23.5% of non-tenure track positions spend the most time on basic research and have an average salary of $99,500 and $71,680 respectively.[15] Of all job types, postdoctoral positions performs the most basic research and have the lowest salary: 42.0% of all postdoctoral positions - increasing to 66.2% at very high research activity institutions - spend the most time on basic research at an average salary of $50,396.[16]

[13] This increase is also observed among engineering new graduates, engineering postdoctoral researchers, and chemistry postdoctoral researchers. (See Appendix Figures B.10 and B.11.)

[14] For example, Janger and Nowotny (2016)'s hypothetical choice survey find that early stage researchers are willing to pay approximately $2,000 for an additional contract year and $4,425 for a 25 percent increase in research autonomy. Using multiple job offers, Stern (2004) finds postdoctoral researchers are willing to take jobs with $16,000 lower salary that allow them to continue research.

[15] Carnegie-Classified "very high research activity" institutions are more likely to spend the most time on basic research at 35.1% for both tenure-track and non-tenure track positions respectively.

[16] The negative correlation between level of basic research and average salary persists across fields. (See Appendix Figures B.12 and B.13.)

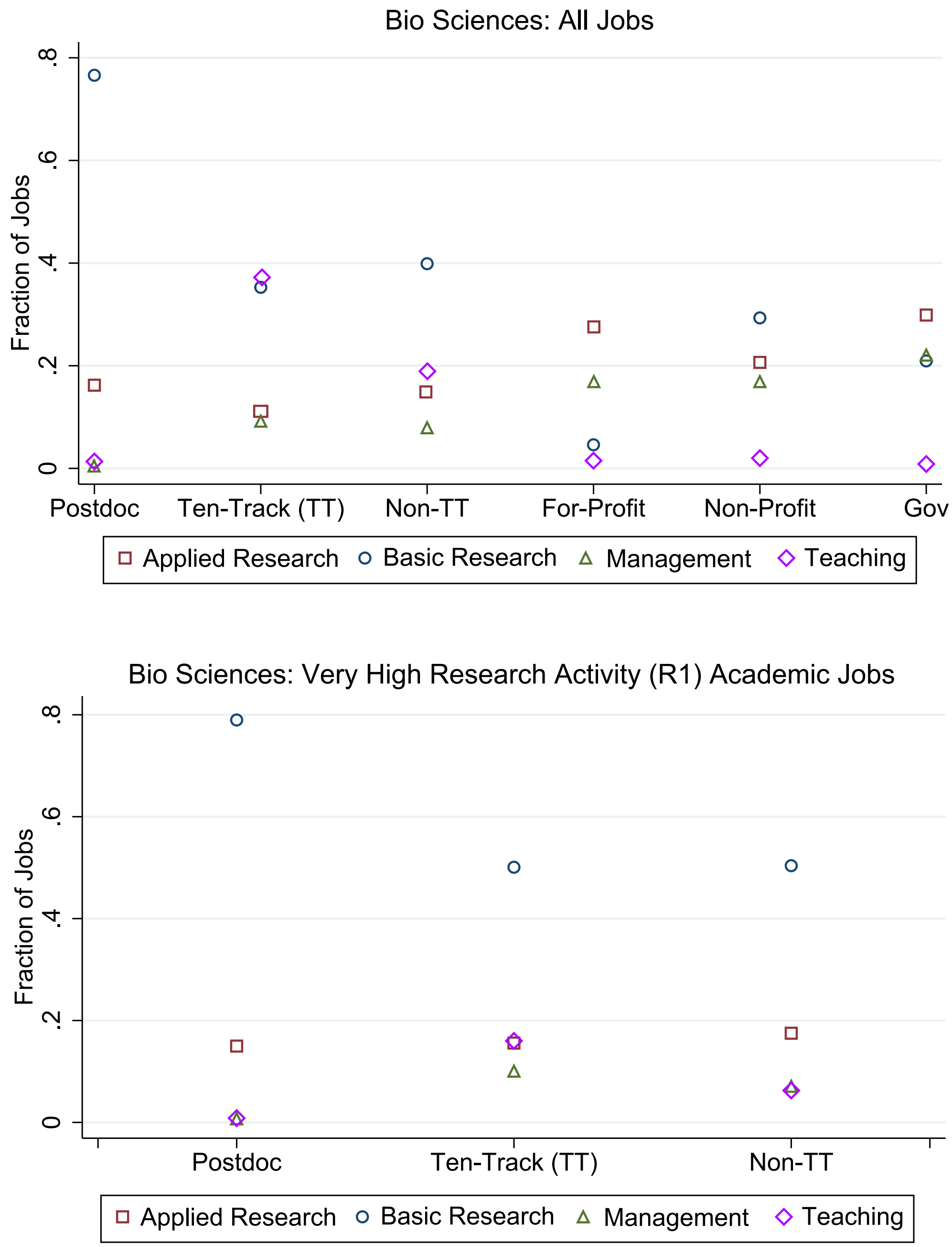


Figure 1.14: Most Common Work Activity by Job Type

Notes: These graphs give the fraction of biological science Ph.Ds. holding each job type during the survey period (1993-2015) that state they spend the most work hours on applied research, basic research, management, or teaching. Bottom graph limits to academic sector jobs (postdoctoral, tenure-track, non-tenure track) at Carnegie-Classified R1 "very high research activity" universities.

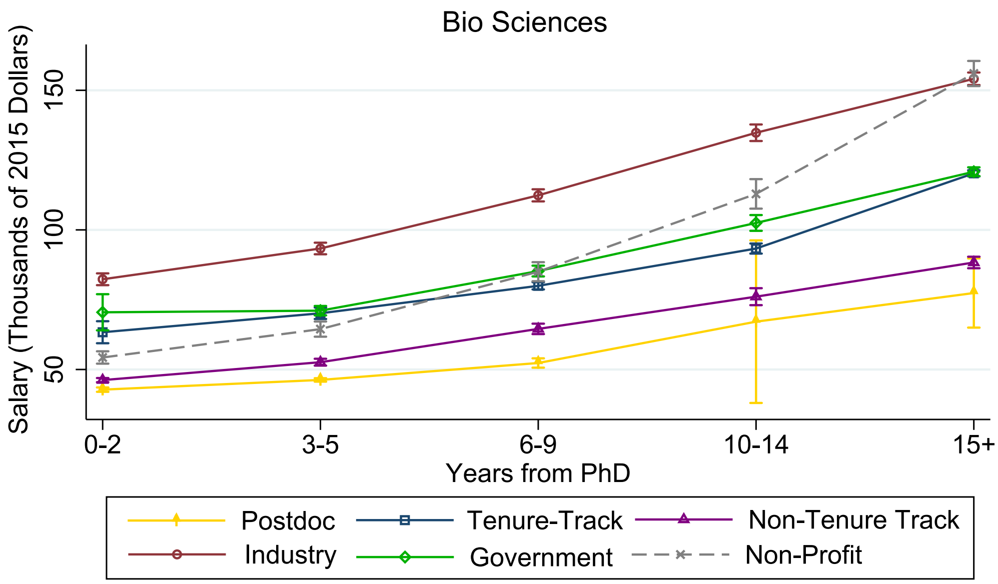


Figure 1.15: Average Salary by Job Type and Career Stage

Notes: This graph gives 95% confidence intervals for the inflation-adjusted salary during the survey period (1993-2015) of biological science Ph.Ds. in six job types - postdoctoral researcher, academic tenure-track, academic non-tenure track, for-profit industry, non-profit, and government - grouped by years since Ph.D. graduation.

Given the limited number of permanent academic positions, a postdoctoral appointment may allow STEM Ph.Ds. the flexibility to wait for high research positions. As shown in Figure 1.16, the postdoctoral appointment is more transitive than the academic tenure-track, non-tenure track, for-profit-industry, government, and non-profit positions. Only 13.3% of STEM postdoctoral researchers remain in these positions for their entire observed career path. Permanent positions act as absorbing states: at least fifty percent in non-postdoctoral job sectors are never observed switching to any other job type.[17] Because individuals do not typically transition between absorbing states, an individual who moves out of academic research to another permanent job type is unlikely to ever return. By remaining in a transitory state like a postdoctoral position, STEM Ph.Ds. have more flexibility to move to any of the permanent job types.

[17]These values are especially high among academic tenure-track (81.5%), academic non-tenure track (76.0%), and for-profit industry (86.2%) positions. 63.1% of government and 55.6% of non-profit employees are never observed transitioning to other job types.

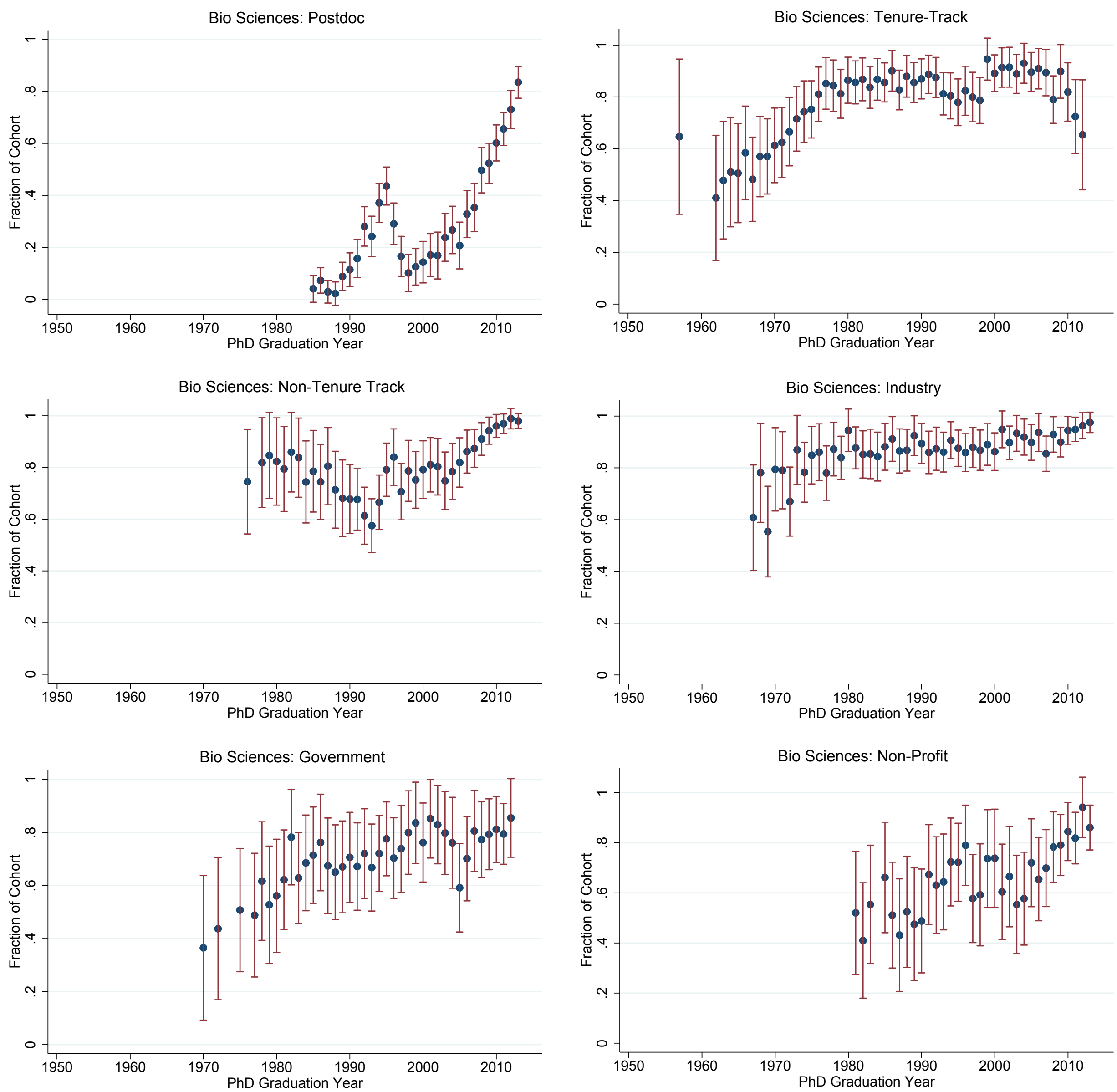


Figure 1.16: Fraction of Individuals Remaining in Same Job Type by Ph.D. Cohort

Notes: These graphs give the three-year moving fraction of each biological Ph.D. cohort observed in each job type that remain in this job type throughout their last observation in the SDR, as a measure of how much the job type is an "absorbing state." Each graph gives the analysis for a different job type: postdoctoral researcher (top left), academic tenure-track (top right), academic non-tenure track (middle left), for-profit industry (middle right), government (bottom left), and non-profit (bottom right). For disclosure purposes, only cohorts with at least 50 individuals and cells with at least 5 individuals are shown.

STEM postdoctoral researchers also spend more time at research-intensive universities than individuals who transition directly from graduate school. 78.7% of first postdoctoral positions are at Carnegie-Classified R1 "very high research activity" institutions. Although postdoctoral researchers are not more likely to transition to any tenure-track position than new graduates, Table 1.6 demonstrates that those who are able to obtain a permanent academic position are more likely to be at very high research activity universities. Among new graduates transitioning to academic positions, 29.5% of tenure-track transitions and 49.5% of non-tenure track transitions are at R1 universities. Among postdoctoral researchers transitioning to academic positions, 51.2% of tenure-track transitions and 67.9% of non-tenure track transitions are at R1 universities. This indicates that individuals pursuing postdoctoral positions are not of lower ability than those who move directly into permanent positions; rather, they may have a higher threshold in the level of research activity they would accept for a permanent position.

Table 1.6: Distribution of Institutions' Carnegie Classifications by Transition Type

	STEM (1)	Bio Sciences (2)	Chemistry (3)	Engineering (4)	Physics (5)
A. Grad To Postdoc					
R1	78.7%	76.3%	80.5%	83.7%	84.4%
R2	6.6%	5.7%	8.0%	7.7%	5.8%
D1	1.6%	1.1%	2.4%	1.6%	2.5%
D2	1.5%	1.4%	1.6%	1.1%	1.6%
Total N	9,297	4,722	820	997	595
B. Grad to Tenure-Track					
R1	29.5%	23.6%	4.3%	44.2%	13.5%
R2	10.4%	5.0%	4.0%	13.9%	5.0%
D1	11.6%	7.6%	13.8%	11.6%	6.2%
D2	4.5%	3.5%	4.8%	4.3%	N/A
Total N	5,874	664	256	1,250	158
C. Postdoc to Tenure-Track					
R1	51.2%	50.5%	36.6%	63.4%	57.8%
R2	10.7%	8.4%	10.6%	15.1%	9.3%
D1	6.6%	4.8%	10.2%	6.0%	7.3%
D2	3.2%	3.3%	4.9%	3.7%	2.3%
Total N	5,369	2,083	483	631	312
D. Grad to Non-Tenure Track					
R1	49.5%	54.0%	42.0%	58.5%	58.9%
R2	10.3%	7.2%	7.8%	10.4%	11.1%
D1	5.5%	3.0%	9.2%	6.6%	-
D2	2.3%	2.2%	-	-	-
Total N	2,451	654	111	331	115
E. Postdoc to Non-Tenure Track					
R1	67.9%	65.9%	55.0%	82.1%	76.4%
R2	7.1%	6.4%	6.0%	5.9%	9.1%
D1	3.2%	2.2%	5.9%	2.5%	3.4%
D2	1.0%	0.9%	-	-	-
Total N	2,640	1,108	154	256	188

Notes: This table gives the distribution of known Carnegie Classification among individuals in the overall STEM sample (column 1), biological sciences (column 2), chemistry (column 3), engineering (column 4), and physics (column 5) who have transitioned from A) Ph.D. to postdoctoral appointment, B) Ph.D. directly to tenure-track, C) postdoctoral appointment directly to tenure-track, D) Ph.D. directly to non-tenure track, and E) postdoctoral appointment directly to non-tenure track. For disclosure purposes, only groups representing at least 50 individuals and cells representing at least 5 individuals are given.

"R1 - very high research" awards at least fifty doctoral degrees per year and have at least $40 million in federal research support (e.g. Harvard University, Stony Brook University); "R2 - high research" awards at least fifty doctoral degrees per year and have between $15.5 - $40 million in federal research support (e.g. American University, Eastern Michigan University); "D1 - doctoral I" awards at least fifty doctoral degrees per year and has less than $15.5 million in federal research support (e.g. Drake University, Indiana State University); and "D2 - doctoral II" awards between ten to forty doctoral degrees per year (discontinued from classification system in 2000; e.g. Loma Linda University, University of Alabama in Huntsville).

1.4.4 Preferred Research Environment Comes at a Cost

Although postdoctoral researchers are more likely to transition to high-intensity academic research environments, this comes at a significant cost to their lifetime earnings. As postdoctoral researchers transition to permanent job types, they move into positions with equal or higher salaries as individuals who transition directly from graduate school. Figure 1.17 compares the salaries of postdoctoral researchers for the first thirty years after their last postdoctoral appointment to the thirty-year post-Ph.D. salaries of individuals transitioning directly from graduate school. In particular, a tenure-track position after postdoctoral experience has a $2,908 higher salary over the first three years compared to a tenure-track position directly after Ph.D. graduation. This further indicates that postdoctoral researchers are not of lower research ability than those who transition directly from graduate school.

Although postdoctoral experience provides a small improvement in starting salary and growth over time, this does not offset the significant losses from taking a low-paying position early in the career. Figure 1.18 gives the average thirty-year post-Ph.D. salaries for individuals who do and do not pursue postdoctoral experience. It can be interpreted as shifting the postdoctoral researchers in Figure 1.17 by the average number of years spent in postdoctoral positions. Over the first thirty years after their Ph.D. graduation, having postdoctoral experience is associated with a decrease of $5,333 (tenure-track), $10,626 (non-tenure track), and $13,549 (industry) in average yearly earnings.

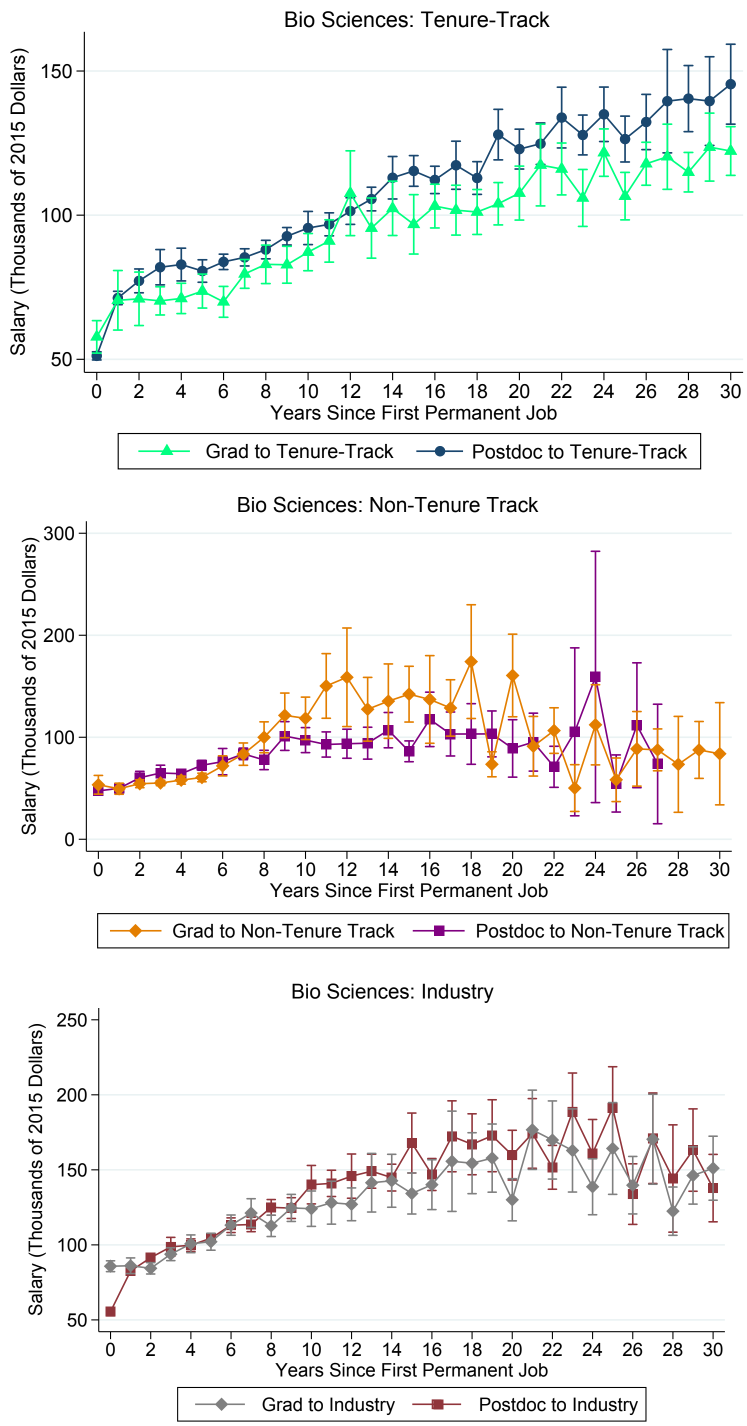


Figure 1.17: Average Salary in Each Year Since First Permanent Job by Postdoctoral Path

Notes: These graphs give the average salary in tenure-track (top), non-tenure track (middle), and industry (bottom) jobs for the first thirty years after starting a non-postdoctoral job type, grouped by whether the individual pursued any postdoctoral experience. The first permanent job year is the Ph.D. graduation year for individuals transitioning directly from graduate school and is the last postdoctoral appointment year for individuals transitioning from a postdoctoral position.

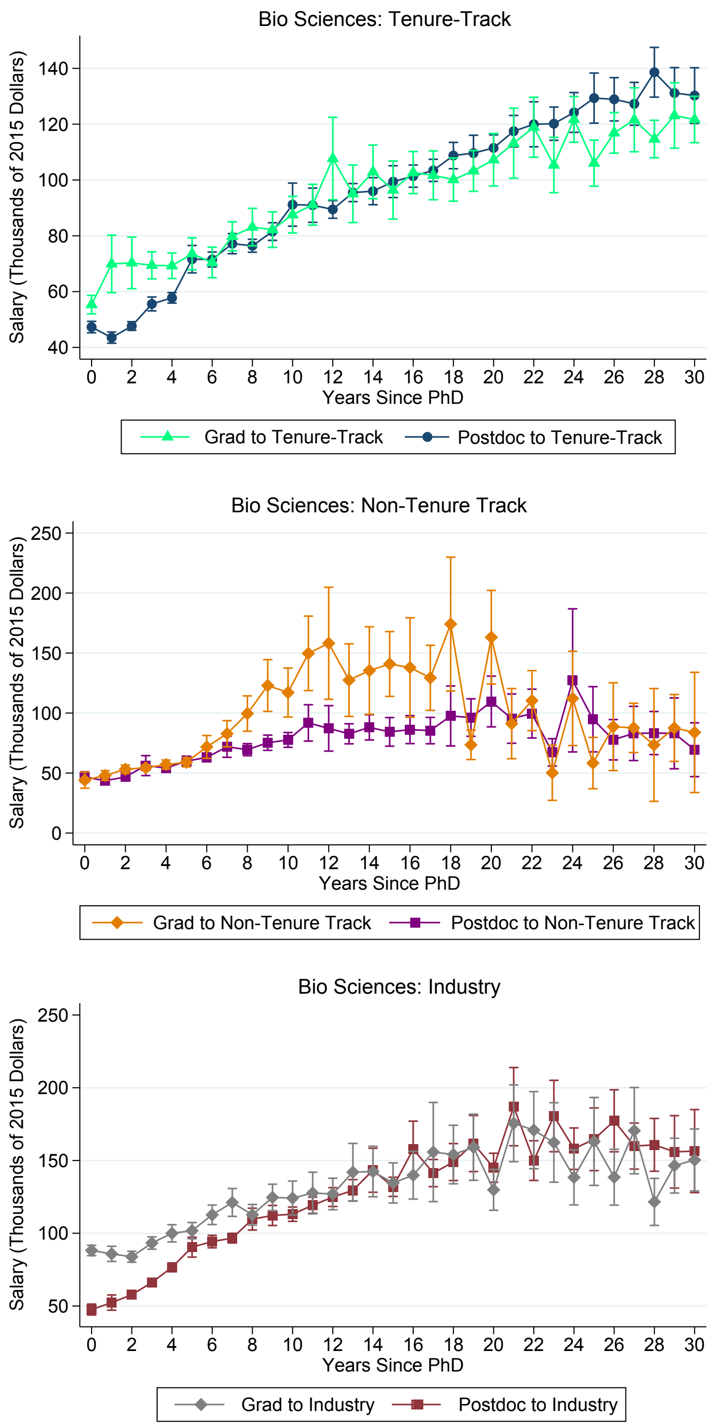


Figure 1.18: Average Salary in Each Year Since Ph.D. Graduation by Postdoctoral Path

Notes: These graphs give the average salary in tenure-track (top), non-tenure track (middle), and industry (bottom) jobs for the first thirty years after Ph.D. graduation, grouped by whether the individual pursued any postdoctoral experience.

To quantify the impact of postdoctoral experience on salary at each career stage, Figure 1.19 gives salary regression coefficients on years of postdoctoral experience for each of the first thirty years post-Ph.D. graduation, as calculated in Equation 1.1. The first few years show a large negative relationship due to the salary gap between postdoctoral appointments and permanent positions. This gap closes as postdoctoral researchers move into permanent positions, but the additional training does not improve their salaries enough to overcome this early loss. As given in Equation 1.2, the average of these yearly coefficients can be interpreted as the postdoctoral deduction in mean lifetime earnings. Rather than provide an education premium, each additional year of postdoctoral experience reduces average lifetime earnings by $3,730.

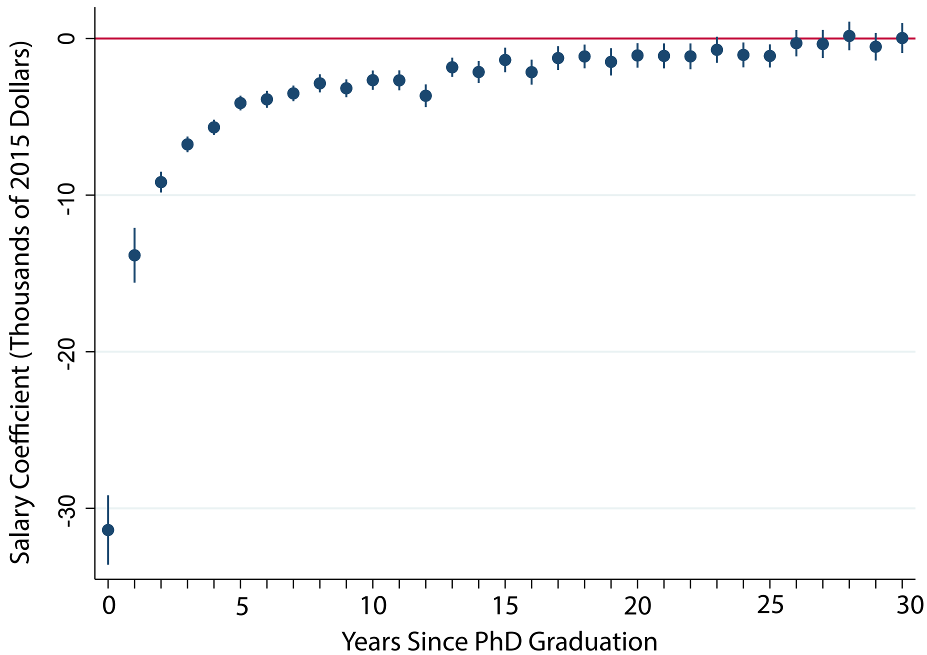


Figure 1.19: Salary Regression Coefficients on Postdoctoral Experience in Each Year Post-Ph.D. Graduation

Notes: This graph gives the salary regression coeficients on years of postdoctoral experience for the first thirty since Ph.D. graduation. Regression includes fixed effects for Ph.D. field of study, graduation year, and job type (tenure-track, non-tenure track, or industry).

1.5 Discussion & Future Work

In this paper, I examine how trends in the STEM labor market have changed over the past fifty years. Using the NSF Survey of Earned Doctorates (SED) linked to the 1993-2015 waves of the NSF Survey of Doctorate Recipients (SDR), I construct career paths for 156,089 U.S. doctoral recipients from 1960-2013 graduation cohorts across six job types - postdoctoral researcher, academic tenure-track, academic non-tenure track, for-profit industry, non-profit, and government - and two employment statuses - unemployed and out of the labor force. This paper contributes to the literature on persistence in STEM academic research, particularly at the postdoctoral level. Due to limited tracking of Ph.D. and postdoctoral outcomes, there has been little previous research on long-term career trends of STEM Ph.Ds.(*Biomedical Workforce Working Group Report* 2012; *Coalition of Next Generation Life Sciences* n.d.; Silva, Mejía, and Watkins, 2019) Using the largest longitudinal survey of U.S. doctoral recipients, this paper creates a comprehensive picture of STEM Ph.D. career paths over time. In doing so, I identify key trends that span multiple Ph.D. fields of study.

Across STEM fields, I find that training time has increased significantly since the 1960's. At the same time, postdoctoral positions are becoming more commonplace even in fields with strong industry ties like engineering. This is despite the declining probability of ever obtaining a tenure-track position in the same time period, ranging from an approximately 14 percentage point decline in chemistry to as much as 36 percentage points in the biological sciences. In recent years, having postdoctoral experience does not significantly improve one's chances of obtaining a tenure-track job: among 2000-2013 cohorts, fewer than 20 percent of both new graduates and postdoctoral researchers transition to these positions.

Rather, I find evidence that postdoctoral positions allow STEM Ph.Ds. to stay longer in high-intensity academic research jobs - but not necessarily ones on the tenure track. Compared to the absorbing states of permanent job types, in which individuals are unlikely to change job sectors, temporary postdoctoral appointments provide STEM Ph.Ds. more flexibility to transition into a new job sector. Although postdoctoral researchers are not more likely to enter a tenure-track position than new Ph.D. graduates, they are 15 percentage points more likely to transition to non-tenure track positions. Like tenure-track positions, more than 20 percent of non-tenure track positions spend the most work hours on basic research, which prior literature demonstrates is a preferred work activity of STEM Ph.Ds.(Agarwal and Ohyama, 2013; Conti and Visentin, 2015; Ganguli and Gaulé, 2018; Janger and Nowotny, 2016; Stern, 2004) Conditional on transitioning to a permanent academic position, postdoctoral researchers are approximately 20 percentage points more likely to take a position at a Carnegie-Classified "very high research activity" institution compared to those who transition directly from graduate school. This indicates that those pursuing postdoctoral positions are not of lower research ability than those transitioning directly from graduate school; rather, they may have a higher preference for academic research jobs. With approximately 79% of postdoctoral positions at very high research activity universities, postdoctoral positions allow individuals to remain in these high-intensity research environments longer.

However, this research opportunity comes at a significant cost in lifetime earnings. Although postdoctoral researchers transition into permanent positions with equal or higher starting salaries as individuals who transition directly from graduate school, their thirty-year salary growth is not large enough to compensate for the low postdoctoral pay early in their careers. Rather than provide an education premium, each additional postdoctoral year is associated with a \$3,730 decrease in undiscounted average of lifetime earnings. This negative salary effect must thus be weighed against the non-pecuniary benefits of postdoctoral positions, in particular the preference for high-intensity academic research, to determine whether it is a worthwhile investment.

Despite the lengthening training and declining probability of ever obtaining a tenure-track position, recent STEM Ph.D. cohorts are more likely to pursue postdoctoral positions than their predecessors. Although these postdoctoral positions do not improve salary over time, they allow STEM Ph.Ds. to remain in preferred high-intensity academic research positions. One potential test for this mechanism is whether the decision to pursue a postdoctoral appointment changes in response to hypothetical or actual shocks to the availability of positions at very high research activity universities. This can be explored in future research using hypothetical choice surveys or labor market shocks. The postdoctoral deduction in lifetime earnings also begs the question of which types of STEM Ph.Ds. are able to afford this cost to pursue the non-pecuniary benefits. Chapter 2 in this dissertation examines how certain time and financial constraints - in particular, women raising children at crucial transitional periods on the academic ladder - may differentially affect the academic persistence of STEM Ph.Ds. If these constraints limit who is able to pursue postdoctoral positions and thus remain in high-intensity academic research environments, it may explain diversity gaps in the STEM pipeline. Examining the factors that drive individuals to pursue postdoctoral positions allows policymakers to better understand the mechanisms driving the STEM labor market. Continuing this work can identify possibilities for improving STEM training programs, encouraging persistence in scientific research across a diverse workforce, and preparing STEM Ph.Ds. for the wide range of career paths they can pursue today.

2 Careers Versus Children

How Childcare Affects the Academic Tenure-Track Gender Gap

2.1 Introduction

As job sectors seek to diversify and reach gender parity, one might consider the biological sciences a success: compared to most science, technology, engineering, and mathematics (STEM) fields, in which women are a distinct minority, women make up the majority of biological science Bachelor's, Master's, and Ph.D. recipients since 2007 (*Science and Engineering Indicators* 2018). Even with these impressive gains in gender parity at the trainee level, women have not progressed up the academic ladder at the same rate: only 35 percent of biological science assistant professors and 17 percent of tenured professors are female (Nelson and Brammer, 2010).

These "leaks" in the biological science pipeline coincide with family formation: 40 percent of women have their first child in the first five years after their Ph.D. graduation. In this paper, I link a biological science Ph.D.'s career path to each year of her children's lives through a novel identification strategy on a longitudinal dataset. Compared to previous literature that correlates the presence of young children with tenure-track gender gaps, this paper isolates the impact that children have on their parents' career trajectories by exploiting the timing of the first child's birth.[18] Consistent with women traditionally taking on the majority of childcare responsibilities, I find that female scientists face a time tradeoff between advancing their highly-competitive careers and raising their young children (Antecol, Bedard, and Stearns, 2018; Bentley and Adamson, 2003; Jolly et al., 2014; Parker and Wang, 2013).[19] After having children, scientist-mothers reduce their work hours and some temporarily leave the labor force - a trend previously documented in other occupations (Azmat and Ferrer, 2015; Bertrand, Goldin, and Katz, 2010).[20] Family-related reasons are by far the most common factor that mothers state for their changes in work situations. Although mothers return to the labor force after their children reach school-age, their reduced working time at the peak of their careers means losing out on important promotions. Comparing characteristics across job types, I find that the high hours needed to move up the tenure track, precisely when mothers have little time to spare, directly contribute to the academic tenure-track gender gap. Despite efforts to improve gender parity at the

[18] Previous literature has typically examined the child effect on parental academic careers by regressing current job type and salary on indicators for children of a certain age (Buffington et al., 2016; Cech and Blair-Loy, 2019; Ginther and Kahn, 2009; Ginther and Kahn, 2014; Kim and Moser, 2020; Mairesse, Pezzoni, and Visentin, 2020; Martinez et al., 2007; Mason, Wolfinger, and Goulden, 2013). This provides a snapshot of correlates to the parent's job type but does not link a change in job type to a change in family formation, as is done in this paper.

[19] The closing of childcare centers during the recent COVID-19 pandemic has exasperated this tension: across job secetors, women's employment and work productivity has steeply fallen as they shoulder the majority of additional childcare responsibilities.(Alon et al., 2020) Within academic research, female principal investigators with a dependent under five years old experienced an over 40 percent decline in research time, compared to 21 percent for all respondents (Myers et al., 2020). This is a likely contributor to female scientists' reduced publication rate during the pandemic, particularly for younger, non-tenured researchers (King and Frederickson, 2020). This may further exasperate the tenure-track gender gap, as Lerchenmueller and Sorenson (2018) find that differences in publication rates explains approximately 60 percent of the gender gap in the biological sciences' academic promotion rates.

[20] This temporary reduction in work force participation in one's thirties - called "a sagging middle" by Goldin and Mitchell (2017) - is observed across the female college-educated labor force.

trainee level, as scientist-mothers leave for jobs with fewer work hours in industry and non-tenure track, a persistent gender gap on the biological sciences tenure track remains.

This paper follows biological science Ph.Ds. surveyed in the National Science Foundation (NSF)'s Survey of Earned Doctorates (SED) linked to the 1993-2015 waves of the Survey of Doctorate Recipients (SDR). This survey represents the largest nationally representative sample of U.S. research doctorate recipients, providing information on a Ph.D.'s total number of children in select age bins, current employment status, and current job characteristics.[21] Using a novel algorithm, I exploit the survey's longitudinal structure to triangulate likely birth years for each child by tracking how a Ph.D.'s total number of children in each age bin changes over time. I then construct the Ph.D.'s career path by identifying each post-Ph.D. year that an individual spends time working in four job types (postdoctoral researcher, academic tenure-track, academic non-tenure track, and for-profit industry) or is out of the labor force.[22] Among individuals who remain in the labor force, I investigate how job characteristics such as self-reported weekly work hours, work activities, salary, and reasons for working change with the timing of their first child's birth.

I find that female biological science Ph.Ds.' career trajectories are significantly altered after their first child's birth. There is no gender gap in tenure-track rates or salary among individuals who never have children or among individuals prior to having children. Starting two years before the birth of their first child, a growing number of female scientists temporarily leave the labor force - peaking at 9 percent out of the labor force by the time their first child is four years old - before returning around the time their first child reaches school-age at six years old. This dip in labor force participation occurs at any point in a woman's career she chooses to have children, whether it's during graduate school to ten years after receiving her Ph.D. Mothers who remain in the labor force reduce their work hours by approximately 12 percent of pre-child hours; comparatively, fathers reduce their work hours by half that amount. This temporary work reduction leads to mothers' permanent losses in promotion and salary. After the first child's birth, the previously negligible tenure-track gender gap starts to widen: by the time their first child is six years old, mothers are 10 percentage points less likely to be in tenure-track positions and have a $5,000 lower annual salary than fathers with children of the same age.[23] These gender gaps persist even as their children grow older and

[21]This includes information on job starting date and comparisons to jobs in previous survey responses, allowing me to infer job status for non-survey years.

[22]This methodology is an expansion of Ginther and Kahn (2017), which estimates postdoctoral experience by creating indicators for each year that a Ph.D. spends any time in a postdoctoral position. Appendix A constructs full career paths across all Ph.D. fields and includes experience in two additional job types (non-profit and government) and one additional employment status (unemployed). These additional employment types represent a small proportion of positions held by the biological science Ph.Ds. in this study and thus are not the focus of this paper's analysis.

[23]As a comparison, this places the biological sciences tenure-track gender gap on par with that of lawyers, another field in which women have become the majority of degree recipients but are underrepresented at the higher ranks of the profession (*A Current Glance at Women in the Law* 2006). Female lawyers with children reduce their work hours by 11 percent, which contributes to the 10 percentage point gender gap on the lawyer partner track (Azmat and Ferrer, 2015).

mothers return to the labor force.

The decline of women observed on the tenure track does not appear in other job types, even within the academic sector, indicating the mechanism is specific to tenure-track positions. Men and women take on postdoctoral and for-profit industry positions at the same rates before and after having children. Among academic non-tenure track positions, the gender gap is the reverse of tenure-track positions: men and women start off in non-tenure track positions at the same rates before having children, but mothers with four-year-old children are 4 percentage points more likely to be in these positions than fathers with children of the same age. Lab-based fields such as the biological scientists are staffed with non-tenure track research positions such as research scientists and lab technicians; thus, these non-tenure track positions have a similar focus on research activities: 39 percent of non-tenure track employees spend the most time on basic research compared to 36 percent of tenure-track employees.[24] There is no evidence of a lower quality research environment off the tenure track: although academic mothers are concentrated in non-tenure track positions, women are as likely to be at a Carnegie-classified "very high research activity" institution as male academics before and after having children.[25] Rather, higher work hours set tenure-track positions apart from other permanent positions, particularly as non-tenure track positions are in the same academic environment. On average, individuals in tenure-track positions work approximately 51 hours per week; individuals in industry and non-tenure track positions work approximately 47 hours per week. The former aligns with women's average pre-child working hours, and the latter aligns with women's average post-child working hours. Thus, the high hours of the tenure track may be pushing off mothers who are time-constrained by childcare. Mothers confirm this career-childcare tradeoff in their survey responses: after having children, women are more likely to list family-related reasons as a factor in changing jobs, working outside their Ph.D. field of study, or not working. Consistent with the prior literature, mothers move into occupations that offer greater worker flexibility and standardized hours like industry and non-tenure track.[26]

Building on previous literature that relies on cross-sectional variation, this paper isolates the impact of having children on the academic tenure-track gender gap by linking the timing of a first child's birth to parental career trajectories. Through a novel identification strategy, I show how a child's birth year can be extracted from repeated observations of grouped family data. I demonstrate that women's reduced

[24] Additionally, 15 percent of non-tenure track employees spend the most time on applied research compared to 10 percent of tenure-track employees.

[25] The Carnegie Classification system groups academic institutions by the number of doctoral degrees conferred and total research expenditures each year. A R1 "very high research activity" institution (e.g. Harvard University, Stony Brook University) confers at least fifty doctoral degrees each year and has at least $40 million in federal research support.

[26] Randomized wage experiments and hypothetical choice surveys find that women are willing to pay twice as much as men to avoid irregular work schedules, particularly if they have children under the age of four (Mas and Pallais, 2017). Historically, professions that have restructured to offer flexible hours and standardized schedules (e.g. medicine, pharmacy, veterinary science) have dramatically increased their gender parity (Goldin and Katz, 2008; Goldin and Katz, 2011; Goldin and Katz, 2016; Goldin, Kerr, et al., 2017; Wasserman, 2016).

labor force participation in their thirties and preferences for standardized work schedules directly ties into time allocations between work and childcare: although women work in occupations with long hours like tenure-track positions at the same rate as men prior to having children, greater childcare responsibility leads mothers to significantly reduce their work hours until their children reach school-age. Losing this work time prods mothers off-track for career promotion and salary raises. Mothers move into industry and non-tenure track positions, which offer similar work activities but are closer to a standard forty-hour work week; these occupations better retain their female workforce by providing amenities valued by mothers. This paper also serves as a cautionary tale for organizations seeking to improve their gender parity: although the biological sciences were successful in dramatically increasing the number of female trainees, structural issues can stop persistence at any point in the career pipeline. By requiring long hours for promotion as women are dedicating time to childcare, the gender gap on the biological sciences tenure track persists today.

The remainder of this paper is organized as follows: Section 2.2 describes the NSF SED-SDR dataset and its advantages in constructing as complete of a description of biological science Ph.D. careers as possible. Section 2.3 summarizes how to exploit the data's longitudinal structure to estimate the birth years of a Ph.D.'s children and construct the parental post-Ph.D. career paths, then details the estimation techniques used to link children and careers together.[27] Section 2.4 presents the main results and evidence for long work hours as the driving mechanism. Section 2.5 discusses potential avenues for future research and concludes.

2.2 Data: NSF Survey of Earned Doctorates (SED) Linked to Survey of Doctorate Recipients (SDR)

This paper draws on the National Science Foundation (NSF)'s Survey of Earned Doctorates (SED) linked to the 1993-2015 waves of the NSF Survey of Doctorate Recipients (SDR). With a full sample of over 124,000 STEM Ph.Ds., the SED-SDR is the largest, nationally representative sample of individuals receiving first-time research doctorates from accredited U.S. institutions in science, engineering, and health fields.[28] The survey starts following individuals the year they apply for their Ph.D. graduation in the SED, then checks in with respondents on a roughly biennial basis in the SDR waves until they reach the age of 76, emigrate from the U.S.,[29] or are otherwise unable to respond.[30]

[27] Further detail on these methodologies are given in Appendices A (career paths) and C (child birth years).

[28] Table 1.2 in the previous chapter gives the full distribution of fields. This paper focuses on Ph.D. fields categorized by the NSF as "biological/biomedical sciences."

[29] Starting in 2010, the survey expanded to include U.S. research doctorate earners residing outside of the U.S. through the International SDR (ISDR). However, given limited data on expats, this project focuses on individuals who obtained their Ph.Ds. in the U.S. and remain in the U.S.

[30] This consists of individuals who are known to be deceased, terminally ill, incapacitated, or permanently institutionalized in a correctional or health care facility.

Each survey collects extensive information on the doctoral recipient's individual demographics, family structure, and job characteristics. Respondents give the number of children living in their household as part of their family in the following age bins: "under 6", "6-11", "12-17", and "18+" (1993 wave); "under 2", "2-5", "6-11", "12-17", and "18+" (1995-2001 waves); and "under 2", "2-5", "6-11", "12-18", and "19+" (2003-2015 waves). Thus, a single wave may only narrow a Ph.D.'s children's ages between two to seven years; however, the survey's longitudinal structure can follow the children's ages over time. The survey also asks respondents about their employment status and - if employed - their start date, job sector, most common work activities, average hours worked, and annual salary. For individuals who have changed jobs since the previous survey wave or are no longer in the labor force, the survey asks their reasons for doing so; individuals can check as many reasons as apply. This extensive questioning allows for the tracking of job characteristics over time, building a detailed picture of the Ph.D.'s career.

Overall, the response rate for each SDR wave is approximately 70 percent (Foley, 2015). As shown in the previous chapter, Table 1.1 gives a comparison between the number of waves an individual is expected to have responded to the SDR (based on their Ph.D. graduation year and age) to the actual number of waves an individual is observed in the SDR. Because many individuals only respond to one SDR survey wave, the traditional longitudinal strategy of using individual fixed effects to look at within-person outcomes may not hold. Instead, this paper uses as much information provided to fill in an individual's career path and triangulate their children's birth years. I focus instead on trends at the group-level, using individual characteristics as controls. Thus, this methodology is less reliant on an individual's response rate and benefits from the high overall response rate. However, it still holds that the fewer waves an individual contributes to the SDR, the less accurate their children's birth years can be estimated and the less complete their career path can be constructed.

2.3 Methodology

2.3.1 Estimating Child Birth Years and Constructing Career Paths

I exploit the longitudinal structure of the SDR to estimate a Ph.D.'s total number of children and the likely birth years for each child.[31] First, I identify a Ph.D.'s total number of children. Because each SDR wave asks for the number of children in the household, it does not include children who may have left the household - for example, to go to college. By examining how the number of children in the household changes across survey waves, I determine the total number of children a Ph.D. ever has by keeping track of the number of children leaving the household, remaining in the household, and recently born.

[31]For more detail on the algorithm and a hypothetical example using this methodolgy, see Appendix C.

Once a Ph.D.'s total number of children is identified, I construct an algorithm to estimate the likely birth years for each child. First, I split the total number of children into individual child indicators in each age bin. One key assumption is that children increase in age and leave the household in chronological order. In other words, the oldest child leaves the household first, and new children are younger than already observed children. Thus, the leftmost indicator is attributed to the youngest child, and the rightmost indicator is attributed to the oldest child. If this assumption fails, an indicator may be falsely attributed to the wrong child. For a large enough age difference between the two children, the incorrect information pulls down the possible age range for the older child and may lead to estimation errors.[32] However, without further information from the survey, I would be unable to identify the correct child.

I then determine the birth years that fall within each child's set of age indicators across survey waves. Table 2.1 gives the range of estimated first child's birth years for all STEM Ph.Ds. and for biological science Ph.Ds. who graduate in the 1990's.

Table 2.1: Range of First Child's Likely Birth Years

	STEM (1)	Bio Sciences (2)
Error: <0 years	4.7%	4.7%
1 year	25.4%	24.2%
2 years	31.6%	35.0%
3 years	2.4%	2.3%
4 years	12.8%	13.5%
5 years	0.5%	0.5%
6 years	13.3%	12.9%
7 years	9.2%	7.1%
Number of Children	52,225	13,494

Notes: This table gives the distribution of first child's likely birth year ranges for the full STEM sample (column 1) and for biological sciences (column 2). Row 1 gives the percent that have a negative range, with the start year of the range occuring after the end year. Rows 2-7 indicate the number of years that are identified as being likely birth years of first children.

I restrict to 1990-1999 Ph.D. graduation years for analysis, as it gives the largest sample of cohorts observed for at least ten years. In the majority of cases, the algorithm reduces the first child's likely birth down to one or two years. A small percent of individuals have an error in which the estimated range's start year is later than the end year. As previously stated, this can occur if a younger child leaves the household before their older sibling - thus incorrectly contributing their age indicator to another child.[33] The larger birth year ranges at four, six, and seven years correspond with the range of the age indicators "2-5", "6-11", "12-17", and "12-18"; in these cases, respondents may have only answered one survey in the time they have

[32] Because the main analyses focus on the oldest child, this error would tend to underestimate the first child's age. However, this direction of error would still estimate a child effect, potentially shifting from a "birth" effect to a "toddler" effect.

[33] As a robustness check, I have re-run the analysis after removing all individuals for which this type of error occurs; this does not significantly impact the results.

children. Without further information, I cannot reduce the ranges below those given by the survey.

To determine the concurrent parental job in each year, I construct career paths across six job types and two non-employed statuses.[34] In each post-Ph.D. year, I determine whether an individual spends any portion of that year in the job type or employment status of interest. I then use this information to construct employment type indicators for each year from an individual's Ph.D. graduation to their last survey response. This analysis focuses on the five most prevalent positions that Ph.D. parents hold: postdoctoral researcher, academic tenure-track, academic non-tenure track, for-profit industry, and out of the labor force. For survey years, I pull job characteristics such as work hours, work activities, and salary to more fully describe an individual's job in that year.[35] If the respondent has changed positions since the previous survey wave or is out of the labor force, I also pull their reasons for changing work situations.

2.3.2 Linking Children to Careers

Before describing the main analyses, I present summary statistics for the sample by gender and parental status. Table 2.2 gives demographics for men and women never observed with children and for men and women ever observed with children. These individual characteristics are relatively balanced across gender and parental status, suggesting the variation I exploit is not confounded by these demographic differences. There are, however, clear gender differences in employment type and job characteristics. Table 2.3 gives summary statistics on experience in each job type and employment status. The gender gap in tenure-track positions for parents is more than twice the gender gap for non-parents, and the gender gap in labor force participation is nearly three times as large for parents as compared to non-parents. Table 2.4 gives summary statistics on job characteristics. The salary gender gap is more than three times larger for parents than non-parents; parents also see larger gender gaps in benefits compared to non-parents. Mothers work fewer hours and are less likely to work full-time than fathers and individuals who never have children. Among individuals who change jobs or are no longer working, Table 2.5 gives reasons for the change in work situations. Mothers are twice as likely as fathers and individuals who never have children to state family-related reasons contributed to their job change or work outside of their Ph.D. field of study. Mothers are over 50 percentage points more likely than fathers and individuals who never have children to leave the labor force due to family.[36]

[34] For more detail on the career path construction and a hypothetical example using this methodology, see Appendix A.1 .

[35] Light interpolation of the individual and job characteristics has been done in between survey years, as described in Appendix A.2. However, job characteristics for the main analyses such as work activities and salary are not interpolated and only use information from survey waves.

[36] Note that respondents can select multiple reasons for their changing work situations. It may be more socially acceptable for women to claim family-related reasons; however, if there are other factors at play, I would expect a higher fraction of women to also select other reasons.

Table 2.2: Individual Characteristics by Gender and Parental Status

	Female, Never Children	Male, Never Children	Diff	Female with Children	Male with Children	Diff
	(1)	(2)	(3)	(4)	(5)	(6)
Race						
White	73.9%	75.4%	-1.5	61.8%	61.1%	0.6
Asian	18.0%	15.5%	2.5	30.1%	31.1%	-0.9
Underrepresented Minority	7.9%	8.4%	-0.5	6.6%	7.0%	-0.5
Citizenship at Ph.D. Graduation						
US Native	74.5%	74.6%	-0.1	63.3%	61.2%	2.1
US Naturalized	4.9%	5.8%	-0.9	3.8%	3.4%	0.4
Research-Intensive						
Bachelor's	51.1%	56.2%	-5.1	51.9%	53.7%	-1.7
Master's	61.2%	63.8%	-2.7	68.8%	56.6%	12.2
Doctorate	79.7%	78.5%	1.1	78.2%	77.0%	1.3
Have Professional Degree	3.5%	5.8%	-2.2	4.0%	8.4%	-4.3
Years in Graduate School	7.4 (2.4)	7.3 (2.4)	0.1	7.1 (2.3)	7.4 (2.5)	-0.3
Number of Individuals	1,570	1,447		2,203	3,108	

Notes: This table gives individual demographics for biological science Ph.D. recipients graduating between 1990-1999, by gender and parental status: race, citizenship, educational prestige (considered by the Carnegie Classification system as a "very high research activity" or R1 university), indicator for having a professional degree by Ph.D. graduation, and years in graduate school (standard deviation in parentheses). Column 1 is among women who never have children. Column 2 is among men who never have children. Column 3 is the female-male difference among individuals who never have children. Column 4 is among women who ever have children. Column 5 is among men who ever have children. Column 6 is the female-male difference among individuals who ever have children.

Table 2.3: Job Type and Employment Status Experience by Gender and Parental Status

	Female, Never Children	Male, Never Children	Diff	Female with Children	Male with Children	Diff
	(1)	(2)	(3)	(4)	(5)	(6)
A. Percent Ever in Position						
Postdoctoral	70.8%	65.0%	5.8	67.7%	66.1%	1.7
Tenure-Track	24.5%	27.9%	-3.4	32.2%	39.3%	-7.1
Non-Tenure Track	29.7%	24.9%	4.9	31.8%	27.1%	4.8
Industry	29.1%	30.3%	-1.3	33.9%	35.1%	-1.2
Not in Labor Force	7.8%	4.0%	3.8	13.7%	3.2%	10.5
B. Average Conditional Years						
Postdoctoral	3.0 (2.3)	3.1 (2.5)	-0.1	3.2 (2.4)	3.2 (2.4)	-0.1
Tenure-Track	9.4 (6.6)	9.2 (6.5)	0.2	9.4 (6.5)	10.5 (6.4)	-1.1
Non-Tenure Track	7.4 (5.6)	6.6 (5.0)	0.9	7.9 (5.8)	7.7 (5.7)	0.2
Industry	7.5 (5.8)	7.4 (5.6)	0.1	8.4 (5.6)	9.3 (6.1)	-0.9
Not in Labor Force	5.2 (3.7)	3.7 (2.8)	1.4	6.0 (4.5)	3.9 (2.7)	2.1
Number of Individuals	1,570	1,447		2,203	3,108	

Notes: Panel A of this table gives the percent of biological science Ph.D. recipients graduating between 1990-1999 who ever hold a certain job type (postdoctoral researcher, tenure-track, non-tenure track, for-profit industry) or are not in labor force by gender and parental status. Conditional on any experience in a certain job type or employment status, Panel B of this table gives the average number of years spent in these positions; standard deviations are given in parentheses. Column 1 is among women who never have children. Column 2 is among men who never have children. Column 3 is the female-male difference among individuals who never have children. Column 4 is among women who ever have children. Column 5 is among men who ever have children. Column 6 is the female-male difference among individuals who ever have children.

Table 2.4: Job Characteristics by Employee Gender and Parental Status

	Female, Never Children	Male, Never Children	Diff	Female with Children	Male with Children	Diff
	(1)	(2)	(3)	(4)	(5)	(6)
Salary (2015 Dollars)	\$70,687 (60,222)	\$75,697 (75,536)	-5,010	\$74,803 (60,763)	\$90,961 (79,712)	-16,158
Benefits						
Health Insurance	89.4%	88.7%	0.8	88.5%	93.5%	-5.0
Pension	77.3%	74.3%	3.0	80.9%	85.4%	-4.5
Profit Sharing	14.6%	12.8%	1.8	15.8%	17.9%	-2.0
Vacation Time	83.3%	85.2%	-1.9	84.3%	88.3%	-4.0
Hours Worked	49.7 (12.6)	50.7 (11.8)	-1.0	45.1 (13.5)	50.5 (11.3)	-5.4
Full Time ($\geq$35 Hours)	93.6%	95.5%	-1.9	87.2%	97.4%	-10.2
Most Frequent Work Activity						
Applied Research	20.0%	19.0%	1.0	19.7%	20.5%	-0.8
Basic Research	33.4%	38.2%	-4.8	29.4%	33.2%	-3.8
Management	10.4%	6.5%	3.9	9.9%	10.0%	-0.1
Teaching	15.1%	15.2%	-0.1	17.6%	13.4%	4.2
Number of Job Observations	12,247	9,504		23,520	35,303	

Notes: This table gives select job characteristics - salary (adjusted for inflation to 2015 dollars; standard deviation in parentheses), benefits, weekly hours (standard deviation in parentheses), and work activities - held by biological science Ph.D. recipients graduating between 1990-1999, by gender and parental status. Column 1 is among women who never have children. Column 2 is among men who never have children. Column 3 is the female-male difference among individuals who never have children. Column 4 is among women who ever have children. Column 5 is among men who ever have children. Column 6 is the female-male difference among individuals who ever have children.

Table 2.5: Reasons for Changing Work Situation

	Female, Never Children	Male, Never Children	Diff	Female with Children	Male with Children	Diff
	(1)	(2)	(3)	(4)	(5)	(6)
A. Change Jobs						
Family	11.1%	6.2%	4.9	20.4%	13.2%	7.2
Career Interests	34.5%	27.6%	6.8	32.4%	31.0%	1.4
Working Conditions	33.5%	28.5%	5.0	34.6%	29.4%	5.2
Pay/Promotion	55.8%	56.4%	-0.6	56.4%	63.0%	-6.6
Location	27.1%	23.4%	3.7	26.5%	25.0%	1.5
Layoff	17.9%	20.5%	-2.6	18.2%	17.1%	1.1
B. Work Outside of Field						
Family	27.3%	20.1%	7.2	52.5%	29.3%	23.2
Career Interests	59.5%	70.8%	-11.3	66.5%	68.7%	-2.2
Working Conditions	46.3%	49.1%	-2.9	61.5%	44.4%	17.1
Pay/Promotion	41.1%	61.3%	-20.2	56.3%	68.5%	-12.1
Location	29.8%	39.1%	-9.3	30.5%	40.4%	-9.8
None Suitable	49.5%	43.8%	5.7	49.7%	40.1%	9.6
C. Not Working						
Family	12.1%	$< 5\%$	> 8	67.9%	15.1%	52.7
Layoff	21.7%	18.5%	3.1	6.9%	30.2%	-23.2
Illness	6.6%	5.5%	1.1	2.7%	5.4%	-2.7
None Suitable	30.4%	33.2%	-2.8	17.0%	33.6%	-16.6
Don't Want to Work	14.0%	10.6%	3.4	30.4%	12.3%	18.0
Number of Observations	33,856	31,257		46,869	67,253	

Notes: This table gives the fraction of individuals who have changed jobs since the previous survey wave (Panel A), work outside their Ph.D. field of study (Panel B), or are not working (Panel C) that attribute the listed reasons for their change in work situation. Survey respondents are able to select as many reasons as apply; thus, the total may be greater than 100%. Column 1 is among women who never have children. Column 2 is among men who never have children. Column 3 is the female-male difference among individuals who never have children. Column 4 is among women who ever have children. Column 5 is among men who ever have children. Column 6 is the female-male difference among individuals who ever have children. For disclosure purposes, cells with fewer than five individuals are approximated.

For the main analyses, I take the median year (rounding down) of each first child's birth year range to give the birth timing.[37] To control for parental career stage, I also combine individuals by the timing of their first child's birth relative to their Ph.D. graduation into four groups: those who never have children, those who have their first child before their Ph.D. graduation, those who have their first child in the first five years post-Ph.D. graduation, and those who have their first child six to ten years post-Ph.D. graduation. A small percent of individuals have their first child more than ten years post-Ph.D. graduation, which I consider outliers and do not include in the main analyses.

Table 2.6 gives summary statistics on the timing of the first child's birth for 1990-1999 graduating cohorts in all STEM fields and specifically in the biological sciences. Many female scientists delay having children until they finish their training: female Ph.Ds. are 10 percentage points less likely than male Ph.Ds. to ever have children, and a larger fraction of mothers wait until they finish their Ph.D. to have children than fathers. Having their first child at 34 years old, the average scientist-mother is also quickly approaching the "advanced maternal age" of 35 (Lean et al., 2017).

[37] By using the median year, I minimize measurement bias as the children's actual birth years would on average be evenly distributed across the survey age bins. As a robustness check, I have re-run analysis using the earliest and the latest year of the birth range; neither robustneses check significantly impact results.

Table 2.6: Parental Characteristics Relative to First Child's Birth

	STEM			Bio Sciences		
	Female	Male	Diff	Female	Male	Diff
	(1)	(2)	(3)	(4)	(5)	(6)
Percent of Ph.Ds.	37.7%	62.3%	-24.6	45.4%	54.6%	-9.2
% Ever Have Children	61.9%	74.3%	-12.4	63.5%	73.9%	-10.4
# Children (If Have Children)	1.9 (1.0)	2.0 (1.0)	-0.1	1.9 (.9)	2.0 (1.0)	-0.1
Timing of First Child						
Parent Age	33.9 (5.2)	34.4 (5.5)	-0.5	33.8 (4.9)	34.4 (5.6)	-0.6
Years Since Ph.D.	1.3 (6.6)	2.1 (6.4)	-0.8	2.2 (5.9)	2.3 (6.3)	-0.1
% Pre-Ph.D. Graduation	30.4%	29.2%	1.2	24.8%	29.5%	-4.7
% 0-5 Years Post-Ph.D.	45.4%	43.0%	2.4	48.6%	41.5%	7.1
% 6-10 Years Post-Ph.D.	19.8%	20.6%	-0.8	21.7%	21.0%	0.7
Number of Observations	36,104			8,445		

Notes: This table gives summary statistics by gender (columns 1 and 4 - female; columns 2 and 5 - male; and columns 3 and 6 - difference between female and male) for the full STEM sample and for the biological sciences, limited to Ph.D. recipients graduating between 1990-1999. The rows give percent of Ph.Ds. that are male or female; percent ever observed with children; average number of children conditional on ever observed with children (standard deviation in parentheses); average Ph.D.'s age at birth of first child (standard deviation in parentheses); average difference between years since Ph.D. graduation and birth of first child (standard deviation in parentheses); percent of Ph.D. parents who have their first child before their Ph.D. graduation; percent of Ph.D. parents who have their first child in the first five years post-Ph.D. graduation; percent of Ph.D. parents who have their first child six to ten years post-Ph.D. graduation; and total number of individuals.

I then link years relative to the first child's estimated birth to the concurrent parental employment type. I examine how the career trajectory changes after having children by comparing the fraction of men and women observed in each employment type in the ten years prior to ten years after having their first child. By comparing pre-trends to post-trends, I limit the observed effect to correlates with the change in family formation. As a further comparison that controls for career stage, I group individuals by the timing of their first child's birth relative to their Ph.D. graduation and examine how the career trajectories for the first ten years post-Ph.D. differ by gender among these groups. Because this analysis is linked to time since Ph.D. rather than time since first child's birth, this also allows for a comparison to individuals who are never observed having children.

To identify the mechanism driving changes in career trajectories, I examine how job characteristics differ across the four job types. With the same methodology I use for the career trajectories, I compare how men and women's average hours worked (conditional on working), employer's research prestige (conditional on working an academic position), and salary (conditional on working) changes before and after having their first child. Among individuals who changed their work situation since the previous survey wave or are out of the labor force, I compare how the fraction that attribute family-related reasons changes before and after having their first child.

Finally, I examine whether the effect remains when controlling for a wide range of individual characteristics on the full STEM sample.[38] I run logit regressions to estimate how time to first child's birth affects the probability that an individual is in each job type or employment status of interest. By separating the coefficients for years before the first child and years after the first child, I allow for pre-birth and post-birth comparisons. I then run regressions with a similar functional form to estimate the impact of the first child's birth on job characteristics. Because job characteristics such as salary can widely differ by sector, I include indicators for the four job types in these regressions.[39] These additional job type indicators control for selection into different occupations, which may confound the child effect.

[38]The controls are race, quadratic age, marital status, marital status interacted with gender, U.S. native citizenship, U.S. naturalized citizenship, time in graduate school, educational prestige (as measured by the Carnegie Classification of one's Bachelor's, Master's, and Doctoral institutions), Ph.D. field of study, and reference year. Using the full STEM sample gives a larger number of observations to support this full set of controls. To account for differences across fields, I include Ph.D. field of study indicators in the regression and cluster standard errors at the Ph.D. field of study.

[39]For example, in the previous chapter, Section 1.4.3 finds that the average tenure-track position pays \$70,142 for the first three to five years post-Ph.D., compared to \$93,344 among for-profit industry positions and \$52,620 among non-tenure track positions.

2.4 Results

2.4.1 Children Derail Mothers' Time in Tenure-Track But Not Other Positions

The gender gap in tenure-track rates lines up with the timing of the first child's birth. Among individuals who are ever observed having children, Figure 2.1 gives no gender gap in the percent holding tenure-track positions in the ten years before the first child's birth.[40] Shortly after the first child's birth, a sizeable tenure-track gender gap of 3.4 percentage points appears and widens to 10.6 percentage points by the time the first child is ten years old.

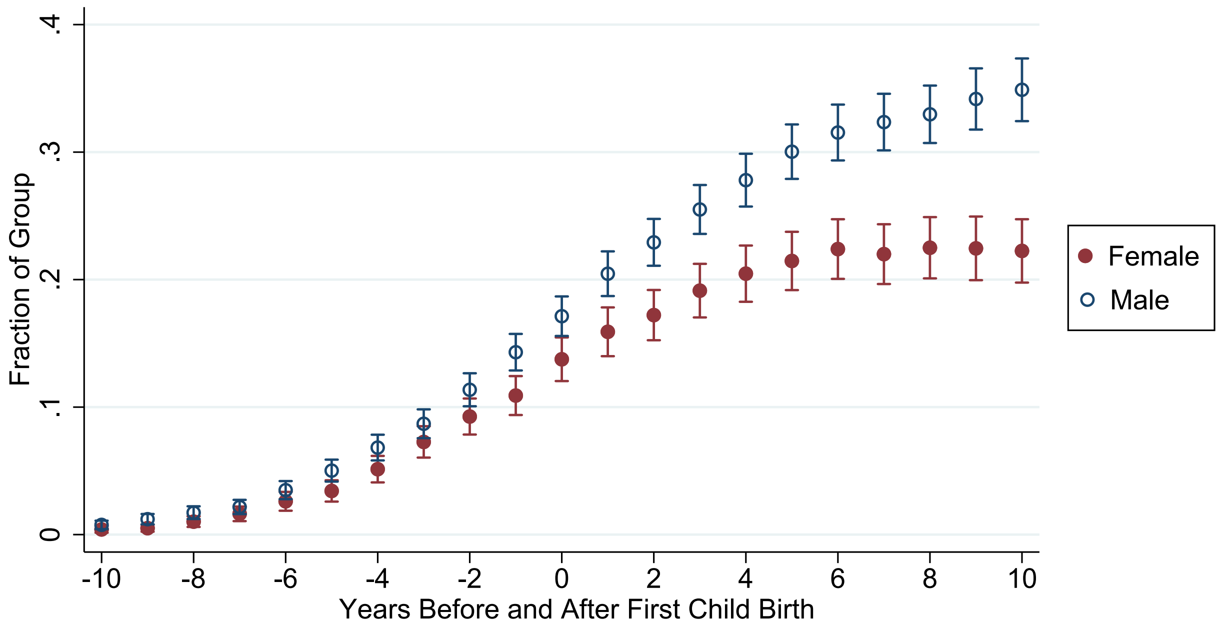


Figure 2.1: Fraction in Tenure-Track Positions Within Ten Years of First Child's Birth by Gender

Notes: These graphs give the raw fraction of male and female biological science Ph.Ds. who become parents that are in tenure-track positions in the ten years before through the ten years after the birth of their first child.

As a comparison, among individuals who are never observed having children, Figure 2.2 shows no consistent gender gap in tenure-track rates through the first ten years post-Ph.D. graduation.

[40]There is a very small significant difference at one year before the first child's birth. This may be an artifact of the child birth estimation, as it is possible to be off by one or more years.

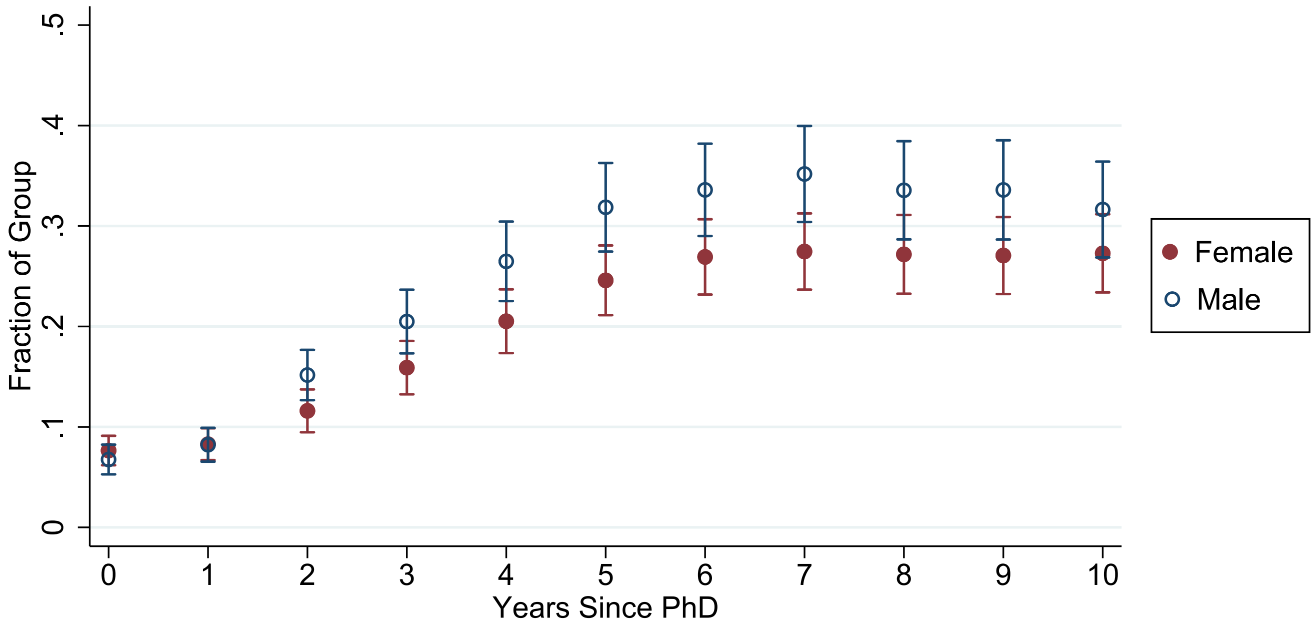


Figure 2.2: Fraction in Tenure-Track Positions During First Ten Years Post-Ph.D. by Gender Among Ph.Ds. with No Children

Notes: These graphs give the raw fraction of male and female biological science Ph.Ds. who never have children that are in tenure-track positions in the first ten years after their Ph.D. graduation.

Controlling for time since Ph.D., Figure 2.3 shows that the tenure-track gender gap is largest among individuals who have their first child within the first five years post-Ph.D., and a smaller delayed gender gap is also observed among individuals who have their first child six to ten years post-Ph.D. This timing lines up with the transition from assistant professorship to full professorship: as shown in Section 1.4.1 of the previous essay, given that the average biological science Ph.D. spends approximately three years in postdoctoral positions, this transition typically occurs three to eight years after their Ph.D. These results remain when controlling for individual characteristics in the Column 2 of Table 2.7. Consistent with prior literature, this regression finds that having children slightly increases fathers' likelihood of being in tenure-track positions compared to their childless peers but does not benefit mothers (Mairesse, Pezzoni, and Visentin, 2020).

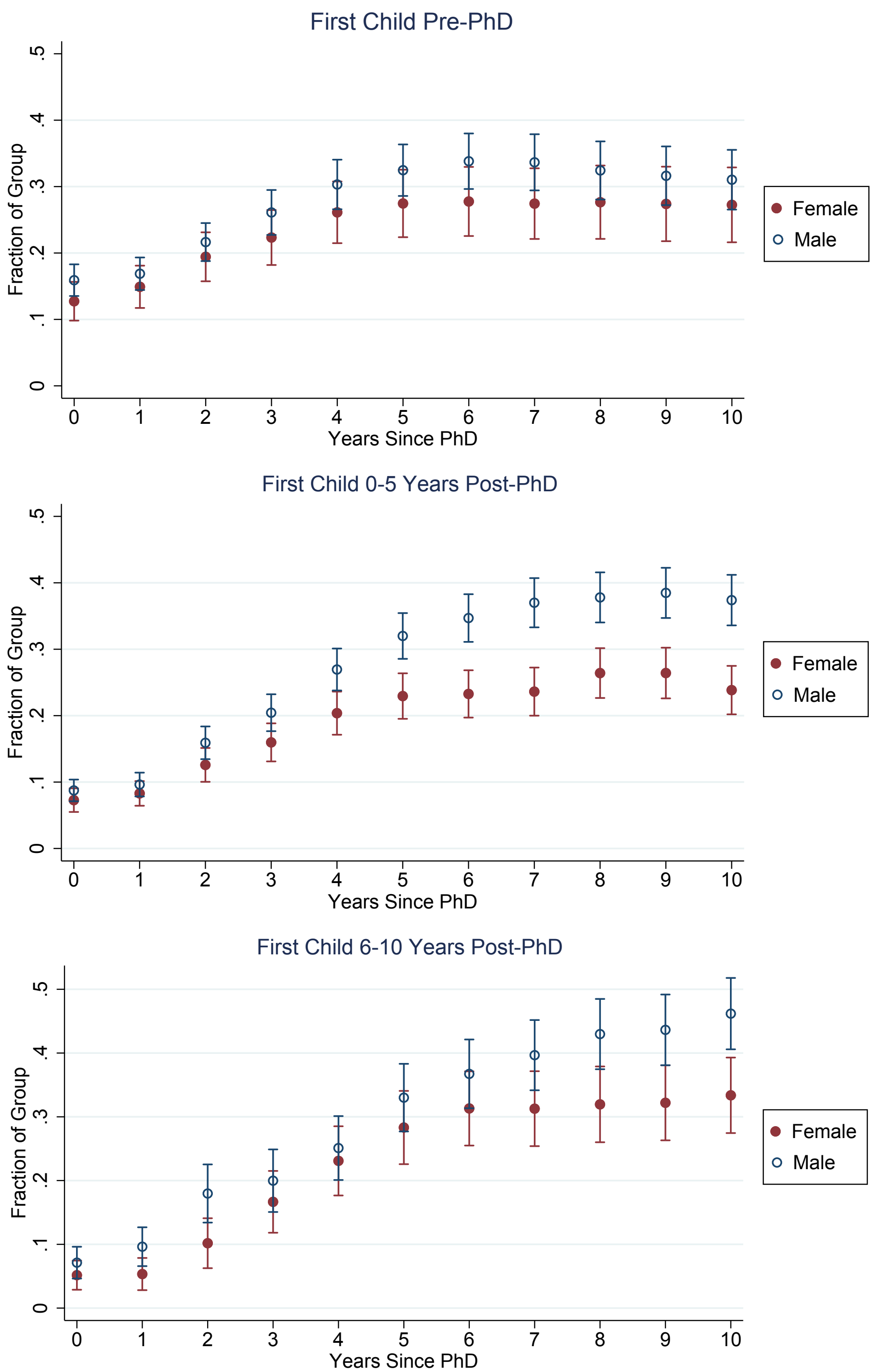


Figure 2.3: Fraction in Tenure-Track Positions During First Ten Years Post-Ph.D. by Gender and Grouped by Timing of First Child

Notes: These graphs give the raw fraction of male and female biological science Ph.Ds. who have their first child before their Ph.D. graduation (top), in the first five years post-Ph.D. graduation (middle), or in six to ten years post-Ph.D. graduation (bottom) that are in tenure-track positions in the first ten years post-Ph.D.

Table 2.7: Logit Regressions of Job Type on Timing of First Child's Birth

	Pr(Postdoc)	Pr(Tenure-Track)	Pr(Non-Tenure Track)	Pr(Industry)	Pr(Not in Labor Force)
	(1)	(2)	(3)	(4)	(5)
Female	-0.04 (0.15)	-0.08 (0.12)	-0.06 (0.11)	-0.19 (0.19)	1.84*** (0.37)
Have Children	-0.14* (0.08)	-0.03 (0.03)	-0.03 (0.09)	0.05 (0.05)	-0.44*** (0.10)
Female*(Have Children)	-0.19** (0.09)	0.07 (0.07)	-0.06 (0.12)	-0.08 (0.09)	0.56*** (0.19)
Years From First Child	0.05** (0.02)	-0.02 (0.02)	-0.01 (0.05)	-0.01 (0.01)	0.04 (0.14)
(Years From First Child)^2	-0.002 (0.001)	0.001 (0.001)	-0.001 (0.003)	-0.001* (0.001)	-0.02 (0.02)
Female*(Years From First Child)	-0.05 (0.04)	0.07*** (0.01)	0.03 (0.05)	-0.004 (0.04)	-0.83*** (0.20)
Female*(Years From First Child)^2	0.002 (0.003)	-0.003*** (0.0008)	-0.004 (0.003)	-0.001 (0.003)	0.06*** (0.02)
Years After First Child	-0.12*** (0.01)	0.03** (0.01)	0.001 (0.05)	0.009 (0.01)	-0.04 (0.13)
(Years After First Child)^2	0.003** (0.001)	-0.001** (0.001)	0.001 (0.003)	0.02 (0.001)	0.02 (0.02)
Female*(Years After First Child)	0.08*** (0.02)	-0.07*** (0.02)	0.02 (0.06)	0.01 (0.04)	0.74*** (0.19)
Female*(Years After First Child)^2	-0.002 (0.001)	0.003*** (0.001)	0.003 (0.003)	0.001 (0.003)	-0.06*** (0.02)
X_{it}	Y	Y	Y	Y	Y
Number of Observations	177,787	177,790	177,783	177,780	173,834

Notes: This table gives logit regression coefficients that correlate the probability of being in a postdoctoral (column 1), tenure-track academic position (column 2), academic non-tenure track position (column 3), industry position (column 4), or not in the labor force (column 5) with gender, parental status, years before having children (given by the absolute years from first child), years after having children (given by the interaction of absolute years from first child and an indicator for after first child's birth), and controls (race, quadratic age, marital status indicator, U.S. citizenship status, time in graduate school, educational prestige, Ph.D. field of study, and reference year). Standard errors given in parentheses and clustered at the Ph.D. field of study level.
* denotes p<0.1, ** denotes p<0.05, *** denotes p<0.01.

The decline of women observed on the tenure track is not observed in other job types, as shown in Figure 2.4. There is no significant gender difference among postdoctoral positions or among for-profit industry positions in the ten years prior to the ten years after an individual's first child's birth.[41] Among individuals in non-tenure track positions, the gender gap is reversed from tenure-track positions: when their first child is four years old, mothers are 4 percentage points more likely than fathers to be in non-tenure track positions. This gap widens to 6 percentage points by the time the first child is ten years old.

As demonstrated in Figure 2.5, these trends hold regardless of the point in a woman's career she chooses to have children, whether that is before obtaining her Ph.D. to ten years out. Controlling for individual characteristics in Table 2.7, there is still no gender gap present among for-profit industry or non-tenure track positions. There is evidence of a temporary gender gap in postdoctoral positions: when their child is first born, mothers are less likely than fathers to be in postdoctoral positions - who in turn are less likely than their childless peers - but mothers return as their first child gets a couple years older. Given the lack of a child penalty for women in other job types, this indicates that a particular characteristic of the tenure track is contributing to its gender gap that is not present in industry or other academic jobs.

[41] If anything, women are slightly more likely to be in postdoctoral positions before their first child's birth, implying that the gender difference in tenure-track positions is not due to scientist-mothers' lack of interest in academic research.

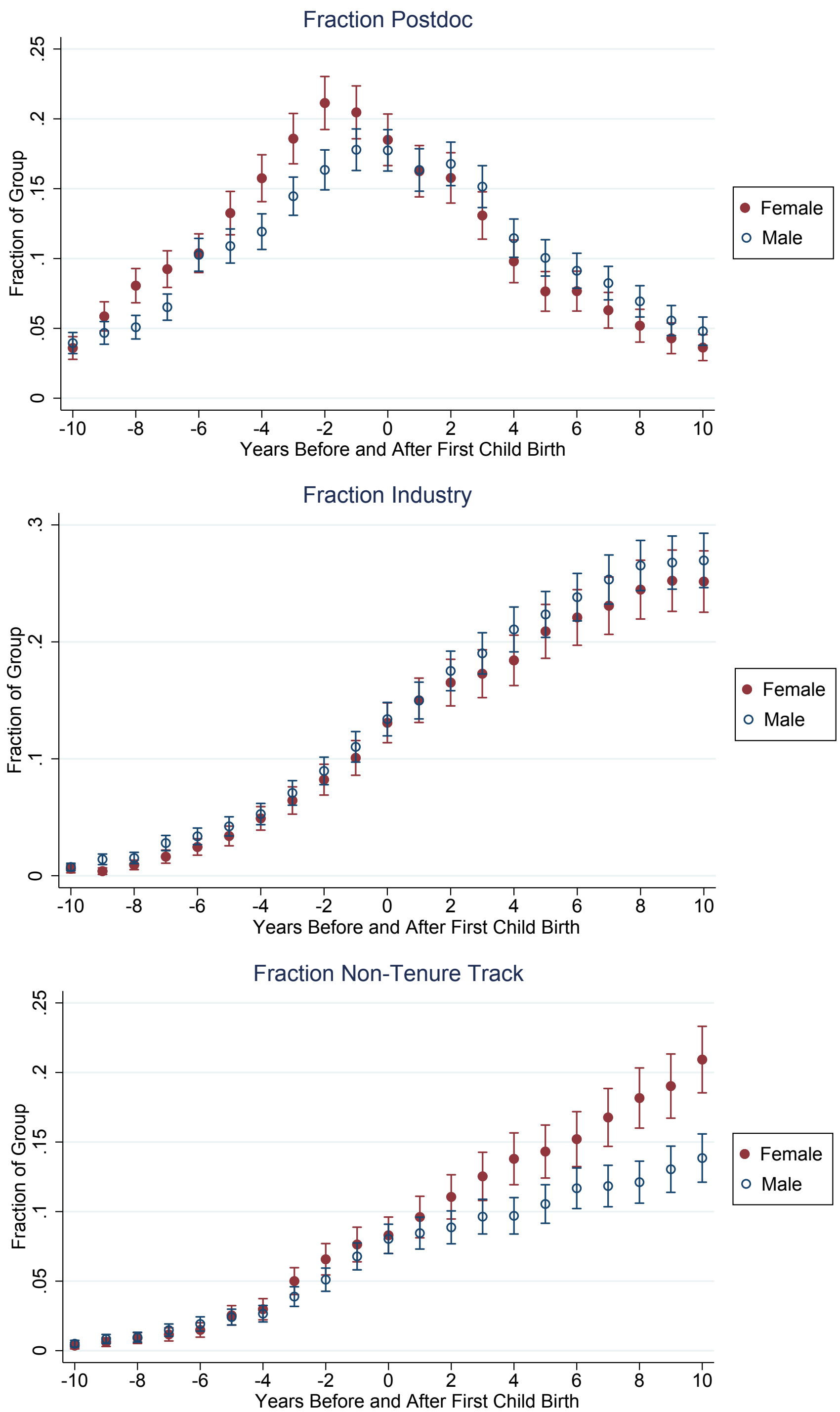


Figure 2.4: Fraction in Select Job Types Within Ten Years of First Child's Birth by Gender

Notes: These graphs give the raw fraction of male and female biological science Ph.Ds. who become parents that are in postdoctoral (top), for-profit industry (middle), and academic non-tenure track (bottom) positions in the ten years before through the ten years after the birth of their first child.

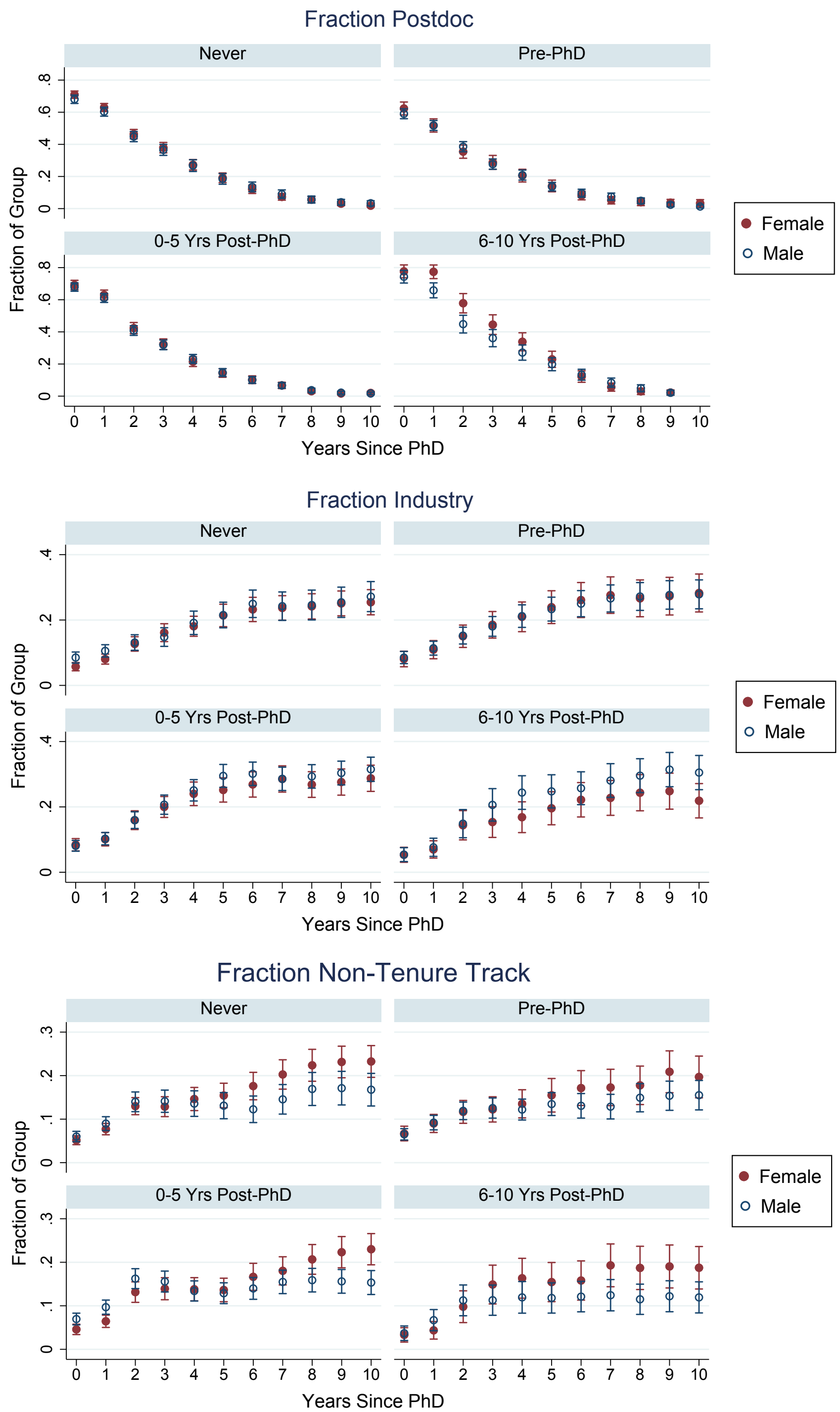


Figure 2.5: Fraction in Select Job Types During First Ten Years Post-Ph.D. by Gender and Grouped by Timing of First Child

Notes: These graphs give the raw fraction of male and female biological science Ph.Ds. that are in postdoctoral (top), for-profit industry (middle), and academic non-tenure track (bottom) positions in first ten years after their Ph.D. graduation, grouped by whether they never have children (top left panel), have their first child before their Ph.D. graduation (top right panel), have their first child in the first five years post-Ph.D. graduation (bottom left panel), or have their first child six to ten years post-Ph.D. graduation (bottom right panel).

2.4.2 Mechanism: Short-Term Reduction in Work, Long-Term Effects on Promotion and Salary

The gender gap observed in tenure-track positions stems from mothers' temporary reduction in work, which conflicts with the job's long hours. Among individuals who never have children, there is no gender gap in the fraction out of the labor force shown in Figure 2.6 or average hours worked shown in Figure 2.7.[42]

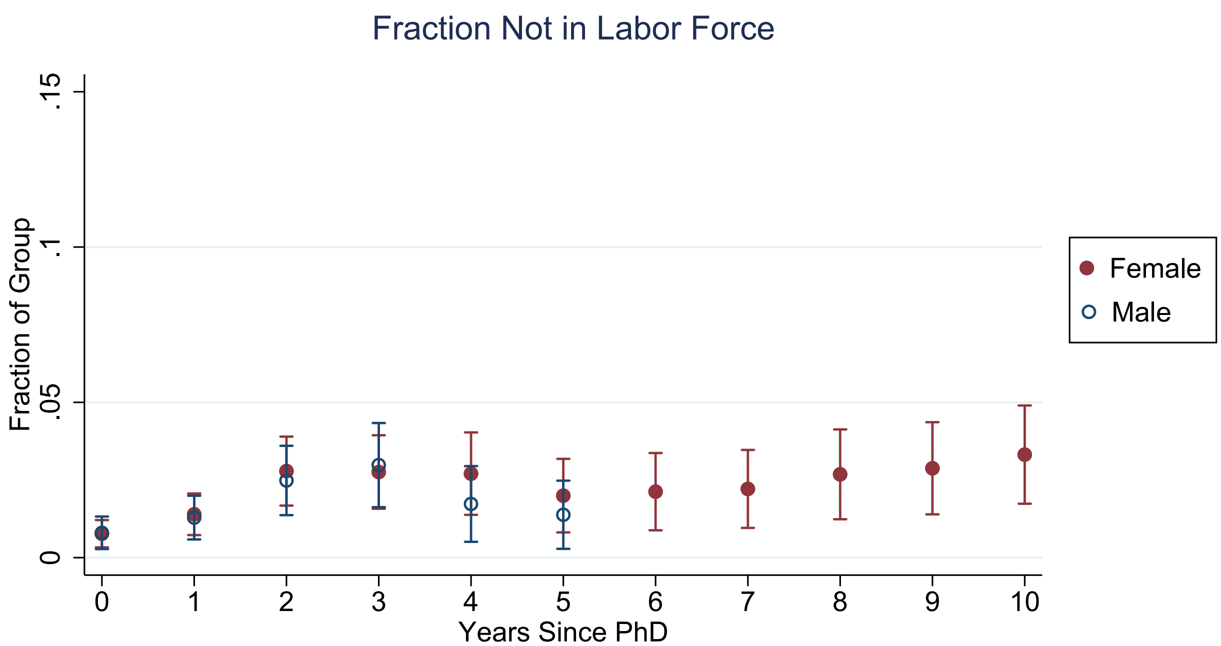


Figure 2.6: Fraction Out of Labor Force During First Ten Years Post-Ph.D. by Gender Among Ph.Ds. with No Children

Notes: This graph give the fraction out of the labor force in the first ten years post-Ph.D. among male and female biological science Ph.Ds. who never have children. For disclosure purposes, only groups with at least fifty individuals and cells with at least five individuals are shown.

[42]For disclosure purposes, small cells are excluded from the graph. For example, the lack of confidence intervals for male Ph.Ds. six to ten years out indicates that very few male Ph.Ds.s who never have children are out of the labor force.

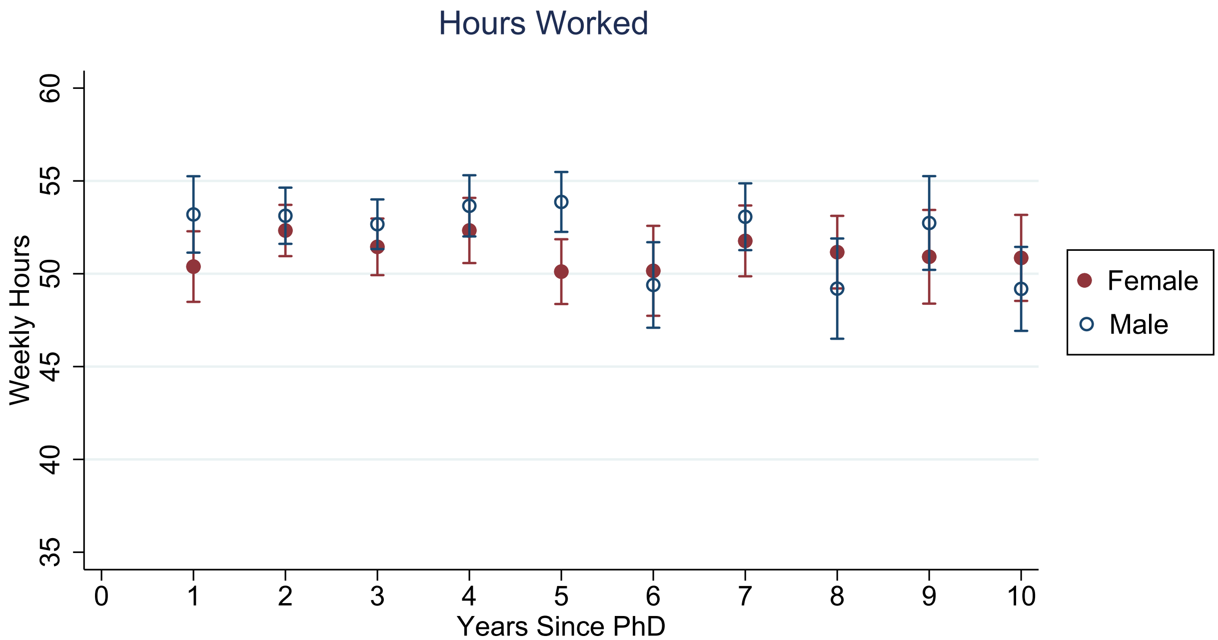


Figure 2.7: Average Hours Worked During First Ten Years Post-Ph.D. by Gender Among Ph.Ds. with No Children

Notes: This graph give the fraction out of the labor force in the first ten years post-Ph.D. among working male and female biological science Ph.Ds. who never have children.

Among individuals observed with children, there is no gender gap prior to the birth of their first child in the fraction out of the labor force shown in Figure 2.8 or average hours worked shown in Figure 2.9. However, women begin to leave the labor force approximately two years before the birth of their first child. Despite their high levels of training, which suggests high attachment to the labor force, 8.9 percent of scientist-mothers leave the labor force in the first four years of their first child's life.

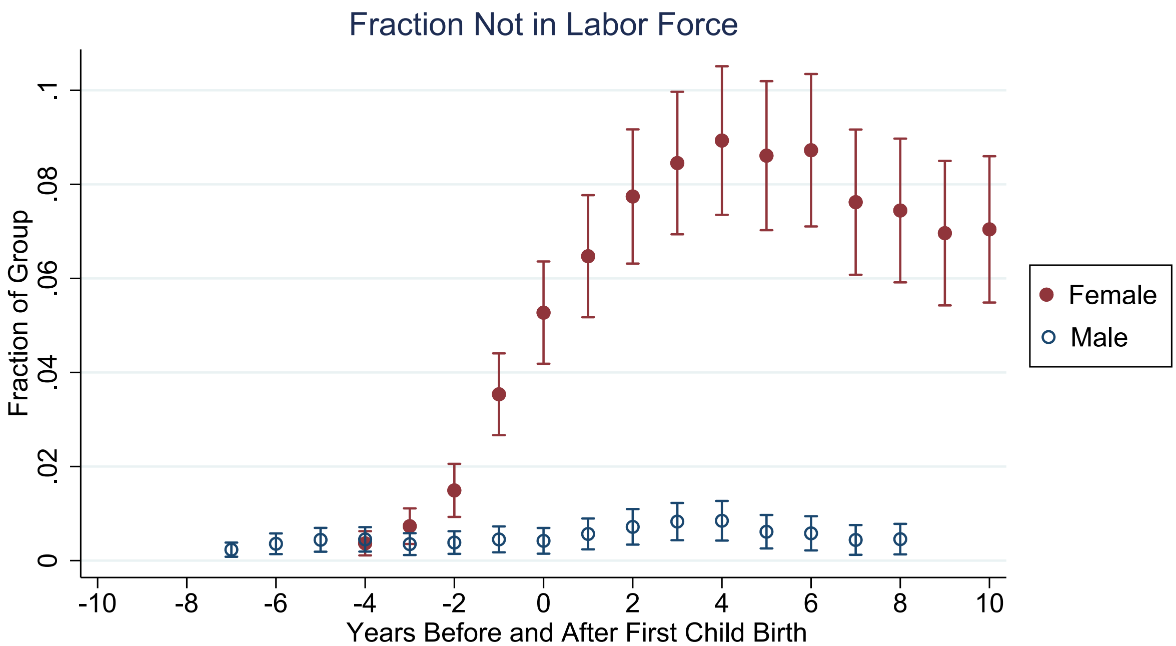


Figure 2.8: Fraction Out of Labor Force Within Ten Years of First Child's Birth by Gender

Notes: This graph give the fraction out of the labor force among male and female biological science Ph.D. parents in the ten years before through the ten years after the birth of their first child. For disclosure purposes, only groups with at least fifty individuals and cells with at least five individuals are shown.

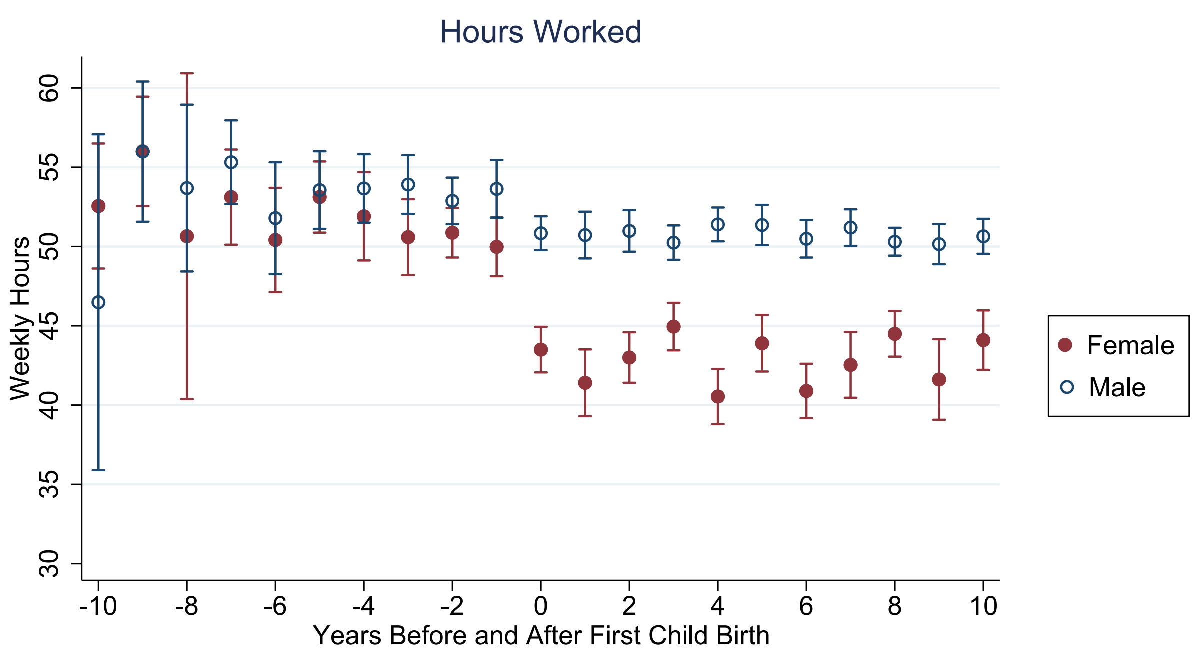


Figure 2.9: Average Hours Worked Within Ten Years of First Child's Birth by Gender

Notes: This graph give the average hours worked among working male and female biological science Ph.D. parents in the ten years before through the ten years after the birth of their first child.

Figure 2.10 shows a majority of mothers list family-related reasons as a factor in this decision to leave the labor force. Like the "sagging middle" described in Goldin and Mitchell (2017), Ph.D. mothers' labor force participation begins to recover once their first child reaches school-age at six years old.

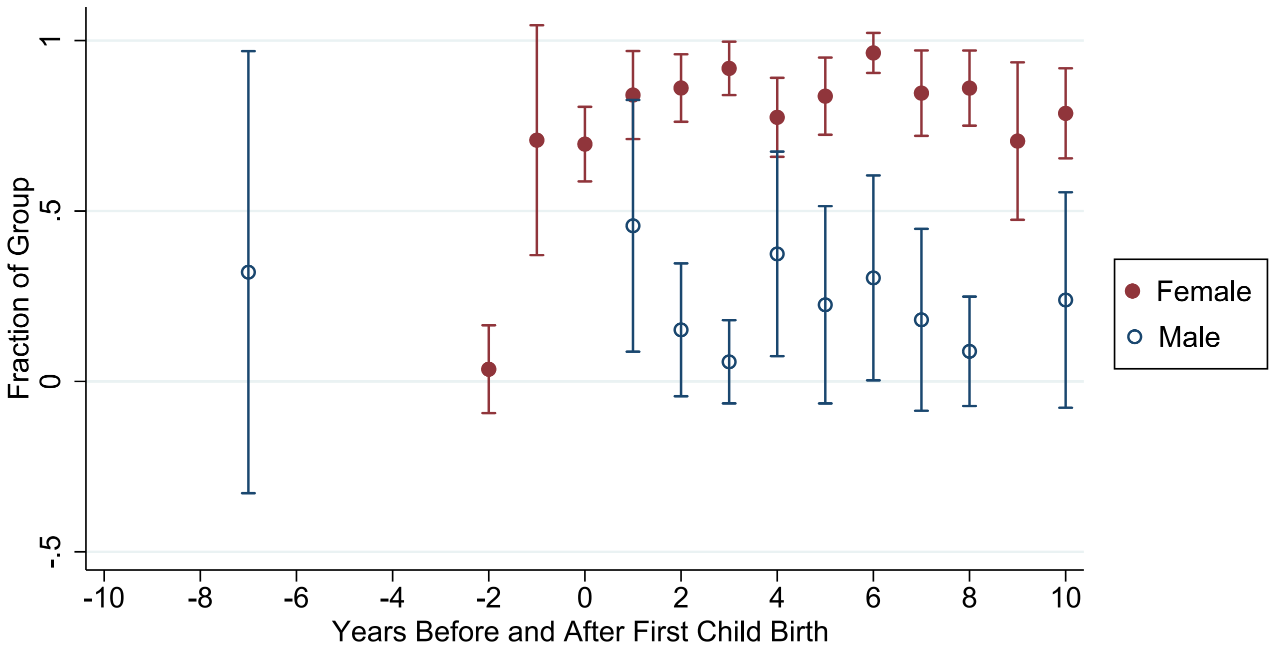


Figure 2.10: Fraction that List Family-Related Reasons for Not Working Within Ten Years of First Child's Birth by Gender

Notes: This graph give the fraction of male and female biological science Ph.D. parents who list family-related reasons as a factor in their decision to not work in the ten years before through the ten years after the birth of their first child.

As shown in Figure 2.11, the hump shape from temporarily leaving the work force appears for all mothers at the time in their careers they choose to have children. Women who have their first child before their Ph.D. graduation experience the hump earliest, peaking approximately 2 years post-Ph.D. Women who have their first child within the first five years post-Ph.D. are next, with their hump's peak at 5 years post-Ph.D. Finally, women who have their first child six to ten years post-Ph.D. have their hump's peak at 7 years post-Ph.D. These results hold when controlling for individual characteristics, as given in Column 5 of Table 2.7: mothers are more likely to be out of the labor force than fathers and their childless peers when they first have children, but this gap closes as their first child gets older.

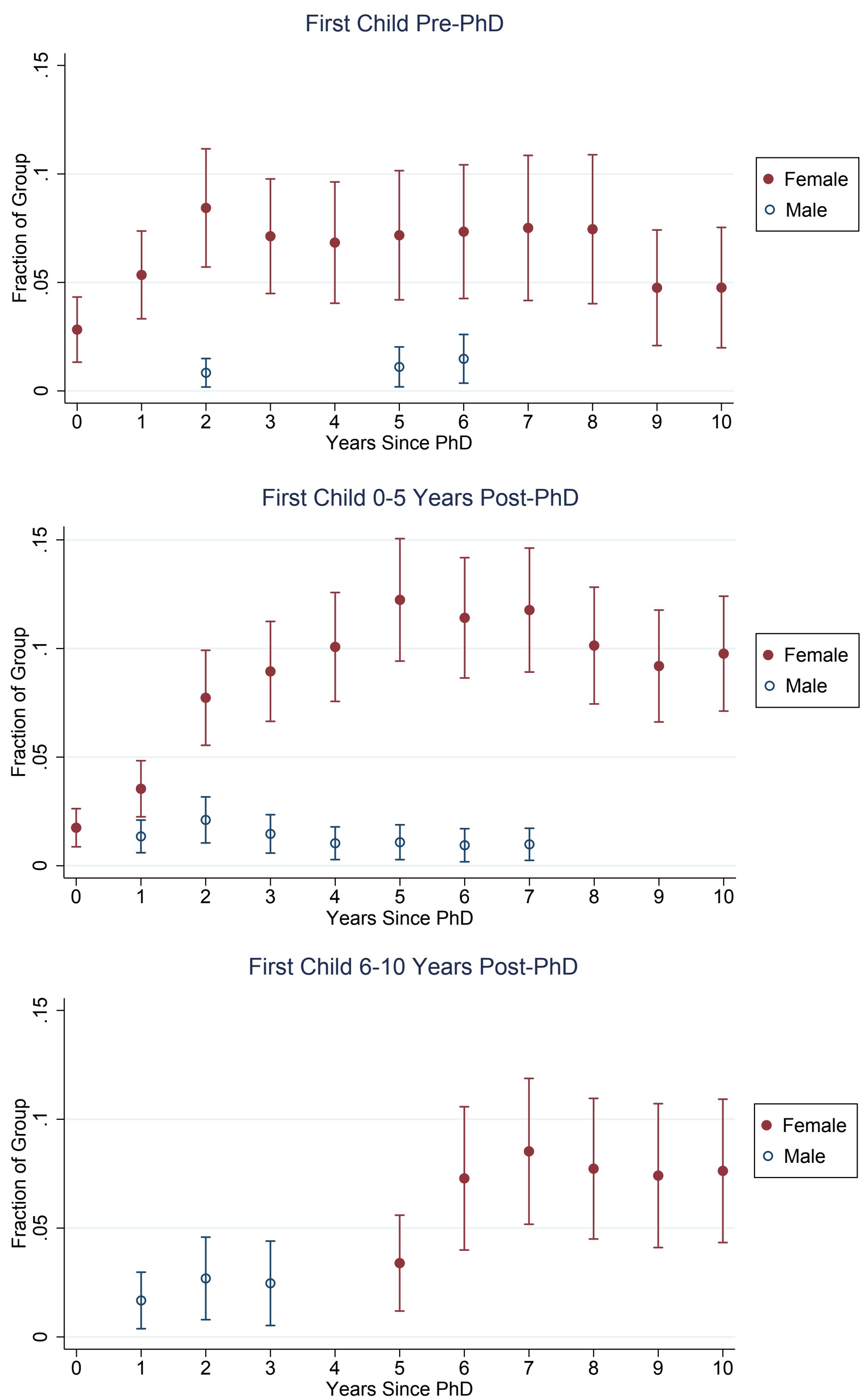


Figure 2.11: Fraction Out of Labor Force During First Ten Years Post-Ph.D. by Gender and Grouped by Timing of First Child

Notes: These graphs give the fraction out of the labor force in the first ten years post-Ph.D. among male and female biological science Ph.D. parents, grouped by whether have their first child before their Ph.D. graduation (top), in the first five years post-Ph.D. graduation (middle), or six to ten years post-Ph.D. graduation (bottom). For disclosure purposes, only groups with at least fifty individuals and cells with at least five individuals are shown.

Individuals who remain in the workforce reduce their work hours after their first child is born. As shown in Figure 2.9, mothers reduce their hours by twice the amount of fathers. This reduction in hours persists through the first ten years of their first child's life. Figure 2.12 shows this gender gap in work hours lines up with the time in a mother's career she chooses to have children. Mothers who have their first child before their Ph.D. graduation consistently work fewer hours than fathers in the first ten years post-Ph.D. Mothers who have children in the first five years post-Ph.D. experience a widening of the working hours gender gap from the Ph.D. graduation, stabilizing at about 5 years out. Mothers who have children six to ten years post-Ph.D. do not experience this working hours gender gap until 6 years post-Ph.D. These results persist when controlling for individual characteristics, as given in Column 1 of Table 2.8: both fathers and mothers reduce their working hours when they have children, but mothers reduce by approximately 3 times as much as fathers.

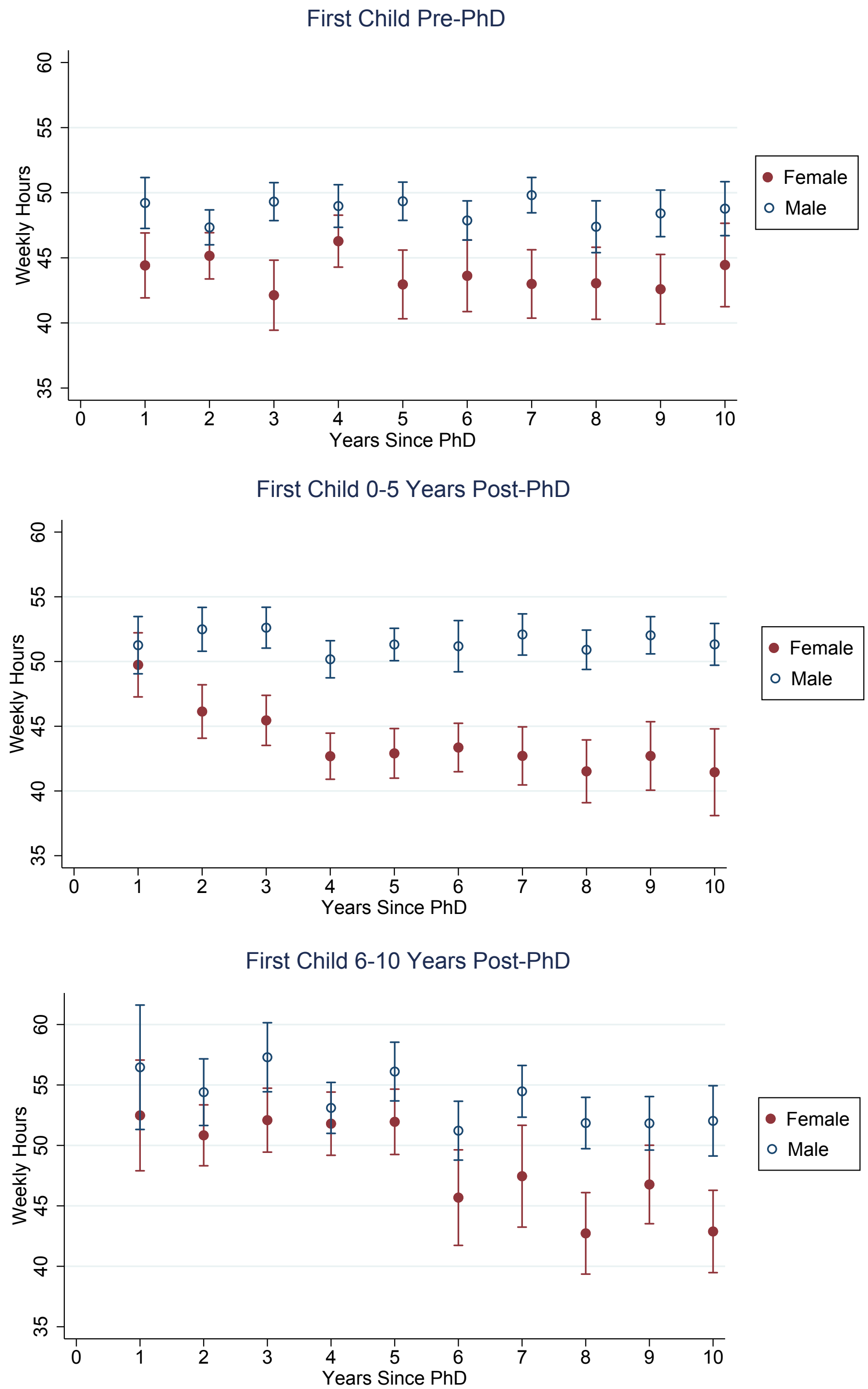


Figure 2.12: Average Hours Worked During First Ten Years Post-Ph.D. by Gender and Grouped by Timing of First Child

Notes: These graphs give the average hours worked in the first ten years post-Ph.D. among working male and female biological science Ph.D. parents, grouped by whether have their first child before their Ph.D. graduation (top), in the first five years post-Ph.D. graduation (middle), or six to ten years post-Ph.D. graduation (bottom).

Table 2.8: Regressions of Job Characteristics on Timing of First Child's Birth

	Hours Worked	Salary	Log Salary
	(1)	(2)	(3)
Female	-3.27** (1.18)	1580.9 (2138.1)	-0.01 (0.03)
Have Children	-0.69*** (0.14)	-721.2 (1781.7)	-0.007 (0.02)
Female*(Have Children)	-1.92*** (0.28)	-5084.3** (1578.6)	-0.07*** (0.01)
Years From First Child	0.63*** (0.14)	1653.3** (684.2)	0.01** (0.01)
(Years From First Child)^2	-0.03 (0.02)	-102.5* (49.5)	-0.0008 (0.0004)
Female*(Years From First Child)	1.52** (0.51)	31.7 (783.2)	0.01 (0.01)
Female*(Years From First Child)^2	-0.14* (0.06)	-28.8 (76.8)	-0.001 (0.001)
Years After First Child	-0.52** (0.17)	-680.0 (666.2)	-0.004 (0.006)
(Years After First Child)^2	0.02 (0.02)	78.1 (46.5)	0.0006 (0.0004)
Female*(Years After First Child)	-1.36** (0.49)	-1100.5 (727.0)	-0.02* (0.01)
Female*(Years After First Child)^2	0.14* (0.06)	57.6 (73.0)	0.002 (0.001)
X_{it}	Y	Y	Y
Job Indicators	Y	Y	Y
Number of Observations	62,097	68,526	68,427

Notes: This table gives regression coefficients that correlate hours worked (column 1), inflation-adjusted salary in 2015 dollars (column 2), and log of inflation-adjusted salary in 2015 dollars (column 3) with gender, parental status, years before having children (given by the absolute years from first child), years after having children (given by the interaction of absolute years from first child and an indicator for after first child's birth), and controls (job type indicators, race, quadratic age, marital status indicator, U.S. citizenship status, time in graduate school, educational prestige, Ph.D. field of study, and reference year). Standard errors given in parentheses and clustered at the Ph.D. field of study level.
* denotes p<0.1, ** denotes p<0.05, *** denotes p<0.01.

Tenure-track positions have the highest average weekly work hours of the permanent job types, as shown in Figure 2.13, and thus are the most affected by the reduced working time. Postdoctoral positions also have high average work hours, which may explain the temporary gender gap observed when controlling for individual characteristics. Because of their temporary nature, long postdoctoral work hours may not be as burdensome to parents as they would be in a permanent position. Comparing the permanent positions, non-tenure track and for-profit industry positions work 4 and 6 fewer hours per week than tenure-track positions respectively. Their average weekly hours are similar to women's reduced work hours after the first child's birth given in Figure 2.9, suggesting that these positions may better align with the schedules of working mothers. Figures 2.14 and 2.15 respectively show that women are more likely to state family-related reasons for their job change or work outside their Ph.D. field of study after having children, further supporting that childcare is driving mothers' job selection.

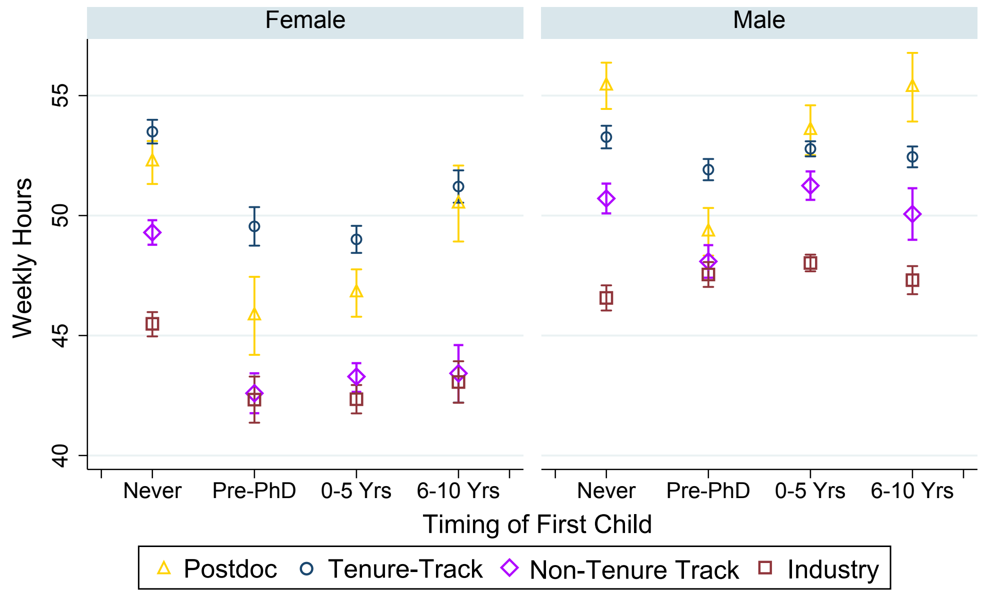


Figure 2.13: Select Job Types' Average Work Hours by Gender and Grouped by Timing of First Child

Notes: This graph gives the average hours worked in four select job types for male and female biological science Ph.Ds. employed in these positions, grouped by whether they never have children, have their first child before their Ph.D. graduation, have their first child in the first five years post-Ph.D. graduation, or have their first child six to ten years post-Ph.D. graduation.

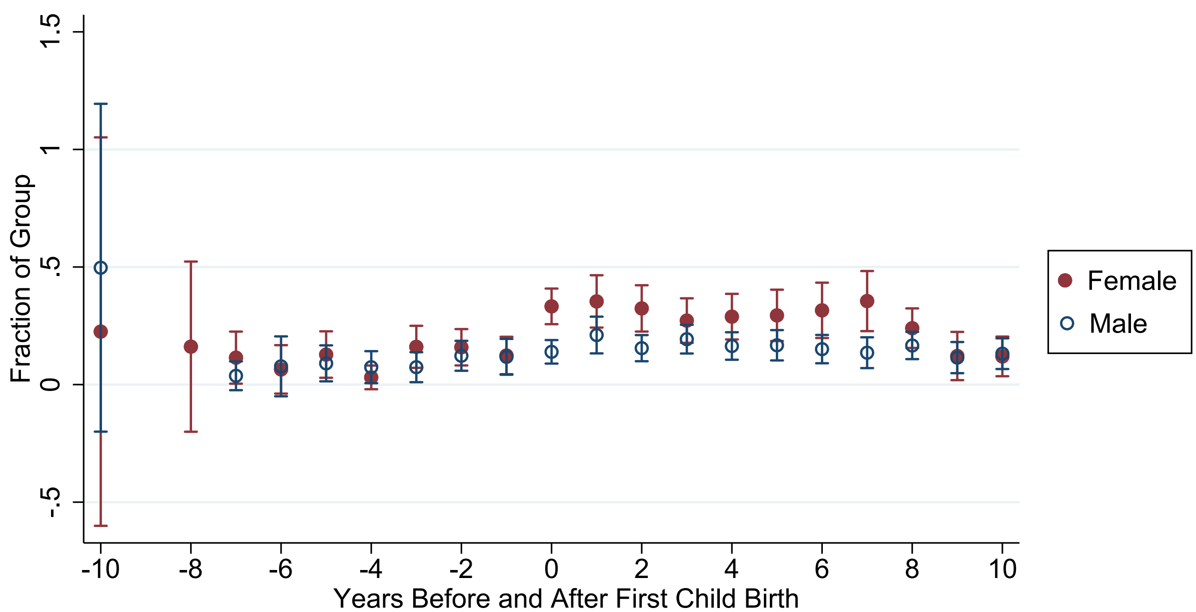


Figure 2.14: Fraction that List Family-Related Reasons for Changing Jobs Within Ten Years of First Child's Birth by Gender

Notes: This graph give the percent of male and female biological science Ph.D. parents who list family-related reasons as a factor in their decision to change jobs in the ten years before through the ten years after the birth of their first child.

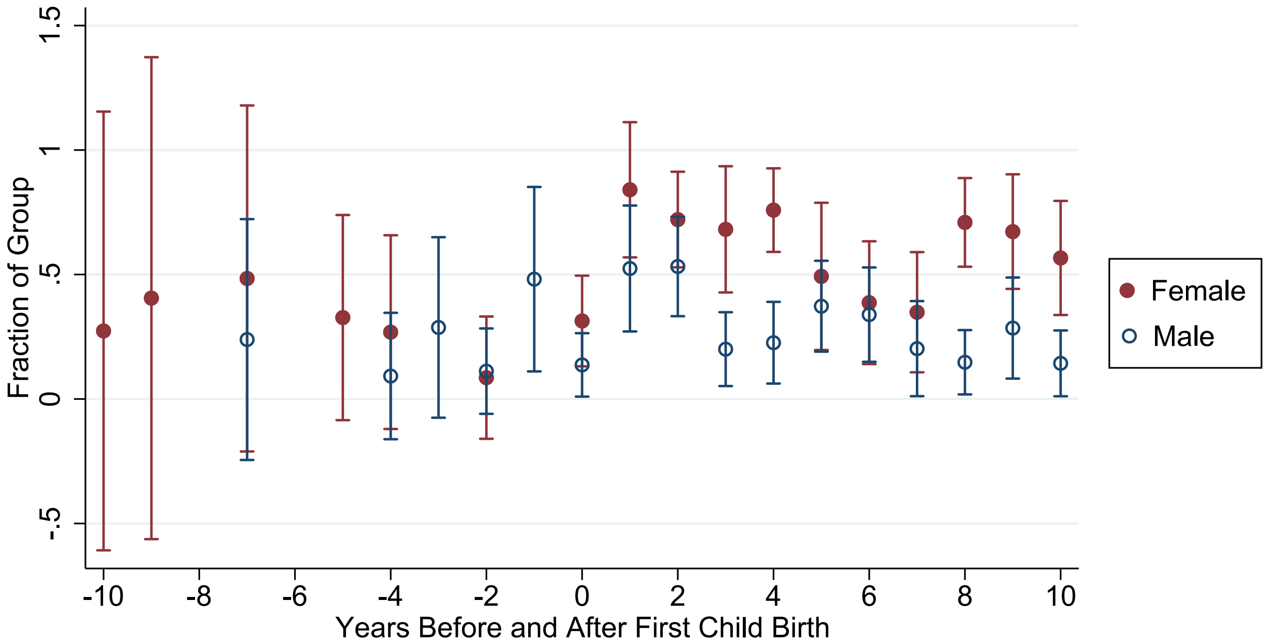


Figure 2.15: Fraction that List Family-Related Reasons for Working Outside Ph.D. Field of Study Within Ten Years of First Child's Birth by Gender

Notes: This graph give the percent of male and female biological science Ph.D. parents who list family-related reasons as a factor in their decision to work outside their Ph.D. field of study in the ten years before through the ten years after the birth of their first child.

Working hours is the most striking difference between tenure-track and other permanent job types in explaining the gender gap. As shown in Figure 2.16, a larger fraction of individuals holding non-tenure track jobs spend the most work hours on basic research and on applied research than individuals in tenure-track jobs. Additionally, non-tenure track jobs are also in the academic sector and share a similar work environment as tenure-track jobs.

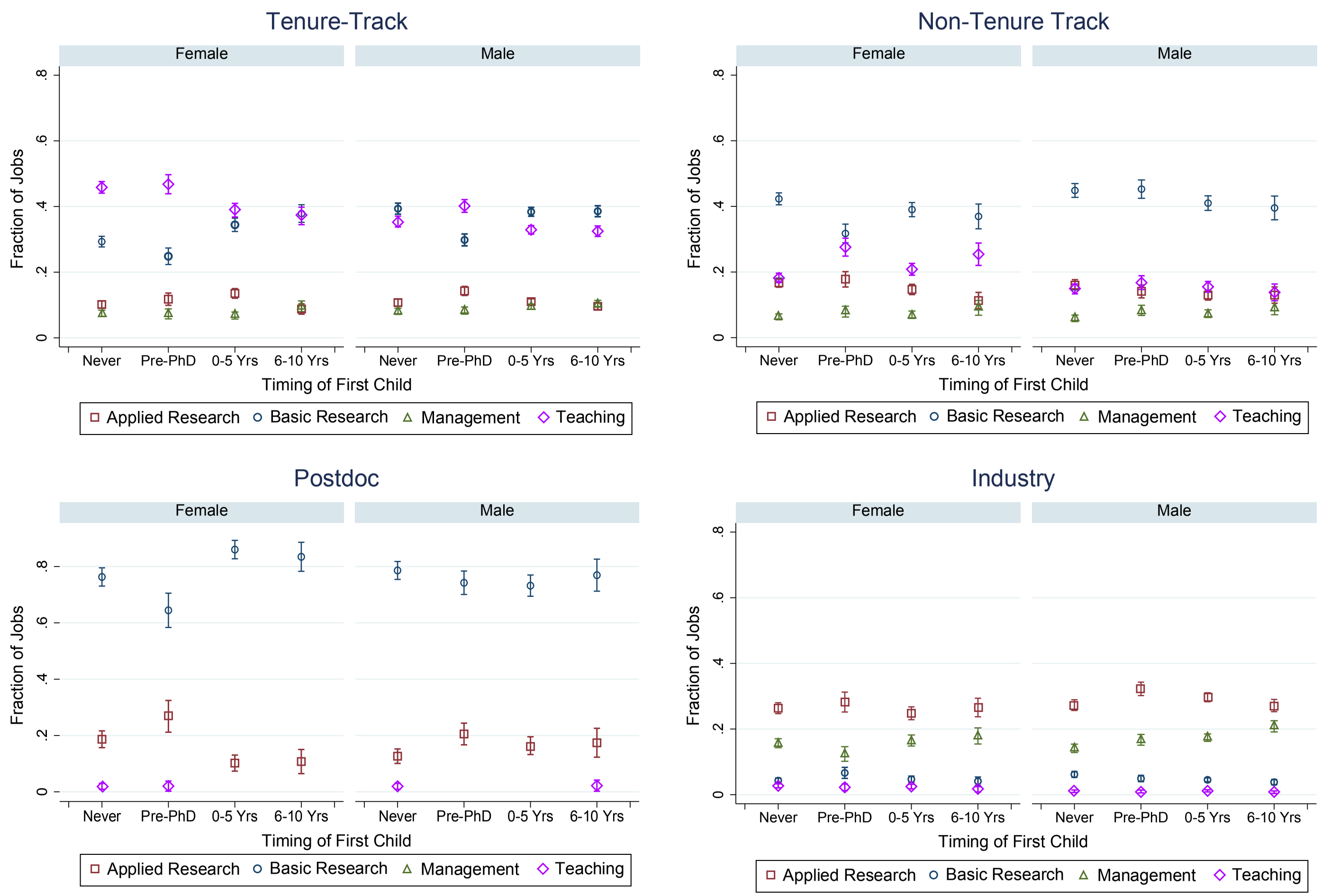


Figure 2.16: Select Job Types' Most Hours Spent Work Activity by Gender and Grouped by Timing of First Child

Notes: This graph gives the fraction of academic tenure-track (top left), academic non-tenure track (top right), postdoctoral (bottom left), and industry (bottom right) positions that spend their most hours on four select work activities for male and female biological science Ph.Ds. employed in these positions, grouped by whether they never have children, have their first child before their Ph.D. graduation, have their first child in the first five years post-Ph.D. graduation, or have their first child six to ten years post-Ph.D. graduation.

Women do not appear to be switching to lower quality research environments in non-tenure track positions: conditional on being in an academic position, Figure 2.17 finds no gender gap in the fraction of individuals in Carnegie-Classified "very high research activity" institutions before and after having children. These results indicate that the mechanism driving the gender gap present in tenure-track positions is not generalizable to the entire academic sector or to research jobs. Rather, the intensity of the tenure track requires longer work hours that may not be amenable to mothers whose time is taken up by childcare.

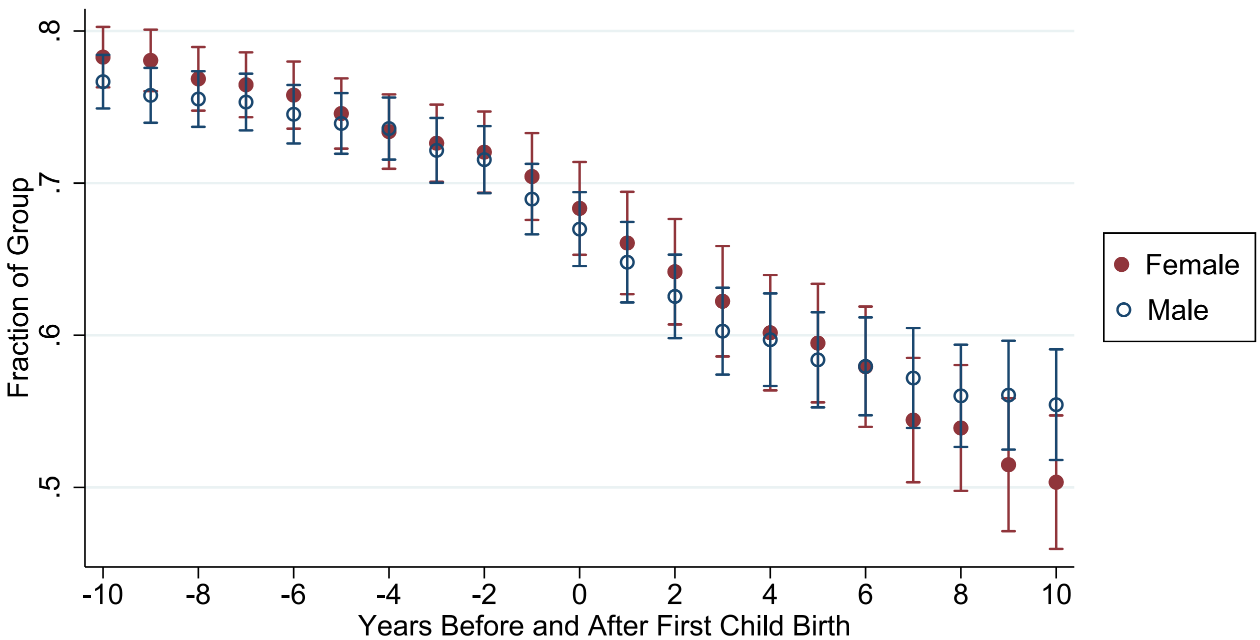


Figure 2.17: Fraction in Carnegie-Classified R1 "Very High Research Activity" Institutions Within Ten Years of First Child's Birth by Gender

Notes: This graph gives the raw fraction in Carnegie-Classified R1 "very high research activitiy" institutions, conditional on being in any academic position (graduate student, postdoctoral researcher, academic tenure-track, and non-tenure track) among male and female biological science Ph.D. parents in the ten years before through the ten years after the birth of their first child.

Mothers' selection into occupations with lower hours is at the cost of fewer promotions and salary raises. A raw comparison of salary in Figure 2.18 masks the gender gap due to mothers' selection into different job types after having children. Once controlling for job type and individual characteristics, a persistent and significant gender gap in salary due to the first child's birth appears in Columns 2 and 3 of Table 2.8. There is no gender gap in salary among individuals who do not have children. Fathers face no child penalty in their salary compared to their childless peers. However, mothers experience a $5,000 lower annual salary than fathers and their childless peers. Using the level-log specification given in Column 3 of Table 2.8, women lose approximately 7 percent of their salary from having children; this salary gap grows by approximately 2 percent each year, even as their children grow older and mothers return to the labor force.

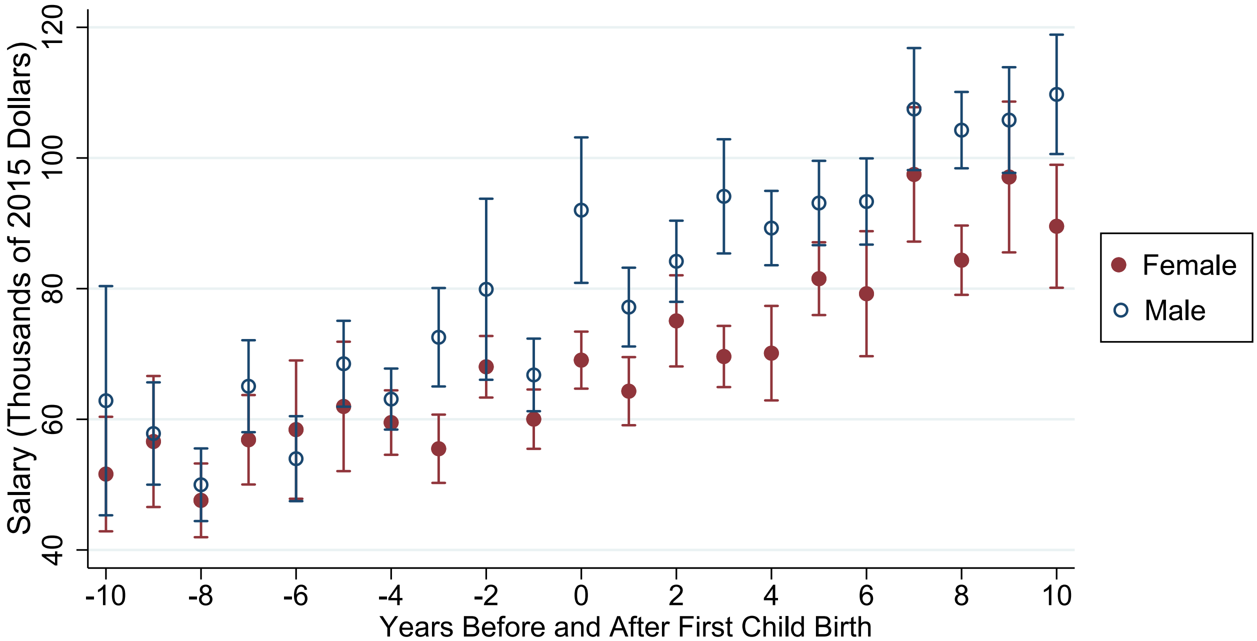


Figure 2.18: Average Inflation-Adjusted Salary Within Ten Years of First Child's Birth by Gender

Notes: This graph gives the raw average salary (adjusted for inflation to 2015 dollars) for working male and female biological science Ph.Ds. who become parents in the ten years prior to ten years after the birth of their first child.

2.5 Discussion & Future Work

In this paper, I examine how having children contributes to the academic tenure-track gender gap through the mechanism of mothers' reduced working time. With a novel identification strategy, I demonstrate how a child's birth year can be extracted from repeated observations of family age data. Using the National Science Foundation (NSF)'s Survey of Earned Doctorates (SED) linked to the 1993-2015 waves of the NSF Survey of Doctorate Recipients (SDR), I estimate the birth years of over 10,000 biological science Ph.Ds.' first children, then match this birth timing to the parent's career path in four job types (postdoctoral researcher, academic tenure-track, academic non-tenure track, and for-profit industry) and one employment status (out of the labor force). Bolstering the cross-sectional correlations found in previous literature, this linkage between the timing of children's birth years and synchronous parental job type isolates the impact that having children has on the biological sciences tenure-track gender gap.

I find that having children shifts female scientists' career trajectories off the tenure track and into less hours-intensive occupations, leading to an over 10 percentage point tenure-track gender gap. Among individuals who never have children, I find no significant difference in the fraction of male and female biological science Ph.Ds. holding tenure-track positions in the first ten years after finishing graduate school. Among individuals who have children, there is no tenure-track gender gap prior to their first child's birth. After their first child is born, 8.9 percent of mothers temporarily leave the labor force; those who remain reduce their working hours by approximately 12 percent. Similar to Goldin and Mitchell (2017)'s findings in the overall female workforce, this "sagging middle" in labor force participation occurs at any point in a scientist-mother's career she chooses to have children.

Although mothers return to the workforce after their children reach school age, this time out of work has long-term effects on mothers in highly-competitive occupations with long hours. After the first child's birth, a gender gap in the percent of individuals holding tenure-track positions appears: by the time their first child is six years old, mothers are 10 percentage points less likely to be in tenure-track positions than fathers. This child penalty for mothers does not appear among individuals holding postdoctoral, for-profit industry, or academic non-tenure track positions. The temporary nature of postdoctoral positions may not significantly affect mothers' choices, as the majority of these individuals have already put off having children until after they finish their training. For the permanent positions, the lower weekly work hours of industry and non-tenure track positions may provide a more family-friendly environment than tenure-track academia. Respondents confirm this career-childcare tradeoff, as women are more likely to attribute changes in their work situation to family-related reasons after having children. Particularly in comparing tenure-track and non-tenure track positions, requiring long hours stands out as the most likely mechanism for the tenure-track gender gap. Non-tenure track positions are slightly more likely than tenure-track positions to spend the most work hours on basic research. There is also no evidence that non-tenure track positions are in lower quality research environments than tenure-track positions: women are as likely as men to be in Carnegie-Classified "very high research activity" institutions despite becoming more highly concentrated in non-tenure track positions after having children. Given that tenure-track and non-tenure track positions share the same academic sector and have a similar focus on basic research, high work hours stand out as the most likely mechanism for pushing mothers off the tenure track.

When mothers take time off work to care for their children, they lose out on the limited number of tenure-track promotions. Consistent with the literature that women value work flexibility and standardized schedules, mothers returning to the labor force move away from tenure-track positions into non-tenure track and industry positions that offer closer to a standard forty-hour work week. However, this more flexible schedule comes at the expense of salary cuts. The gender gap in salary does not close even as children grow older and more mothers return to the labor force. This results in a permanent reduction of women in tenure-track academia and a persistent salary gap, counteracting the many efforts to improve gender equality in the STEM labor force.

Future research will strengthen the link between time allocated to childcare and persistence in tenure-track positions. This may be done by examining the impact of policies (e.g. availability of childcare, access to family planning services, and changes in parental leave) that allow scientist-mothers to more easily balance their children and their careers.[43] Note that prior research examining gender-neutral policies, such as pausing the tenure clock for all parents or providing shareable parental leave, may not be effective in reducing mothers' career-childcare burden.[44] This further indicates the friction stems from the uneven distribution of childcare duties and thus requires a correction geared towards lowering the load on mothers. By examining what factors differentially affect the persistence of women - especially mothers - on the tenure track, policymakers can better correct the leaks in the STEM pipeline and improve diversity in the STEM workforce.

[43] Previous literature has examined policies such as the state-level Paid Family Leave Acts or Targeted Regulation of Abortion Providers in non-academic career settings (e.g. Bennett et al., 2020; Zandberg, 2020).

[44] Antecol, Bedard, and Stearns (2018) find that gender-neutral tenure clock stopping policies actually reduces female tenure rates and substantially increases male tenure rates, because fathers can more quickly return to research. Similarly, Tô (2018) finds that parents - particularly fathers - do not take full advantage of parental leave policies to signal their labor force commitment, leading to lower wages for those who take longer parental leave relative to their coworkers.

3 Where are All the Scientists?

Resources for Studying the Long-Term Careers of STEM Ph.Ds.

3.1 Introduction

A considerable amount of federal funding and time is spent training the next generation of scientists. The U.S. annually appropriates \$2.8-\$3.4 billion on science, technology, engineering, and mathematics (STEM) education programs: two programs alone – the National Science Foundation (NSF)'s Graduate Research Fellowships and the National Institutes of Health (NIH)'s Ruth L. Kirschstein National Research Service Awards – contribute \$332 million on supporting graduate students and \$473 million on supporting postdoctoral researchers respectively.(Granovskiy, 2018) Each year, U.S. universities confer approximately 45,000 STEM doctorate degrees, who spend on average 6.8 years in graduate school.(*Science and Engineering Indicators* 2018) The majority of STEM doctoral recipients then move into postdoctoral appointments, spending on average 2.7 years in these positions.[45]

At the same time, the STEM fields are known for having a "leaky" pipeline: as shown in Section 1.4.2 of an earlier chapter, only 25 percent of 2000-2013 STEM Ph.D. graduating cohorts ever hold a tenure-track position. Approximately 25 percent of biomedical Ph.Ds. hold non-research positions outside of academia, and nearly 50 percent of biomedical Ph.Ds. state their occupation is only somewhat or not at all related to their field of training.(Stephan, 2013) These "leaks" are especially prevalent among underrepresented populations: although women constitute approximately 45 perecent of postdoctoral fellows in the biomedical sciences, they make up approximately 29 percent of tenure-track investigators.(Martinez et al., 2007) Underrepresented minorities make up approximately 11 percent of biomedical postdoctoral fellows but only 6 percent of tenure-track professors.(Meyer et al., 2018) This homogenous workforce - especially at the higher levels - can have a detrimental impact, as previous research demonstrates the importance of diversity on scientific innovation.(Gewin, 2018)

Given the extensive federal funding and time poured into training scientists, it is important to address what factors contribute to the leaky pipeline. Thus far, little attention has been given to the role of graduate programs and postdoctoral appointments on future careers despite the lengthening time that scientists spend in these positions. Even basic information such as the number of postdoctoral researchers at each institution have proven difficult to collect.(*Biomedical Workforce Working Group Report* 2012) This white paper thus has two goals: the first is to compile a list of available resources that can be used in studying the long-term career outcomes of STEM Ph.Ds., and the second is to identify gaps in the literature that could be filled with additional data collection. It is meant to help especially newer meta-researchers evaluate data resources and further encourage the study of STEM Ph.D. careers.

The paper is organized as follows: Section 3.2 describes longitudinal surveys that follow the scientific

[45]See Section 1.4.1 of an earlier chapter for more details.

workforce over time. Section 3.3 describes cross-sectional data that give snapshots of scientist careers at one moment in time. Section 3.4 describes career-related experiments involving STEM doctorates. Section 3.5 describes databases of scientist records. Finally, Section 3.6 concludes with future avenues for data collection and research in scientist careers.

3.2 Longitudinal Surveys

3.2.1 NSF Survey of Earned Doctorates (SED) & Survey of Doctorate Recipients (SDR)

These two surveys combined provide the most longitudinal, comprehensive description of the U.S. scientific trainee workforce. Beginning in 1957, the Survey of Earned Doctorates (SED; formerly called the Doctoral Records File) is an annual census of all individuals receiving research doctorates from accredited U.S. institutions in that academic year.[46] Administered when a student applies for graduation, the survey collects information on doctoral recipients' demographics (including date of birth, country of birth, citizenship, race, sex, marital status, parental status), education through the doctorate, and immediate post-graduation plans. More information about the SED, including annual questionnaires, can be found at https://www.nsf.gov/statistics/srvydoctorates/.

From the SED, a nationally representative subset of individuals receiving their first science, engineering, and health research doctorate is selected to be followed in the longitudinal Survey of Doctorate Recipients (SDR). This biennial survey can be linked to SED responses and asks individuals for updates on their educational history (including additional degrees earned and types of training done), employment (including job changes, occupation, tenure status, salary, compensation, work activities, and satisfaction), and lifestyle (such as marital or parental status changes). Unfortunately, the SDR does not consistently ask about academically focused job characteristics, such as number of publications, patents, and government support.[47] Individuals are followed until they reach 76 years of age (or are otherwise unable to respond). More information about the SDR, including annual questionnaires, can be found at https://www.nsf.gov/statistics/srvydoctoratework/#sd&qs.

The SDR has undergone several changes since its inception in 1973; thus, caution should be used to ensure that longitudinal studies across these survey waves are consistent. Major changes in the 1993 wave make

[46] An earlier version of the DRF for Ph.Ds. graduating between 1920 and 1956 contains limited information on sex, institution, field, and year of doctorate.

[47] A few survey waves (1995, 2001, 2003, and 2008) ask respondents about their five-year publication and patent rates; this question has since been discontinued. No question asks about cumulative number of publications or number of patents.

pre- and post-1993 surveys difficult to compare: the survey layout was reformatted; questions on post-Ph.D. education, current employment, and demographics were reworded and expanded; and the target population was refocused to only include individuals who received U.S. doctorates in science, engineering and health fields.(*1993 Characteristics of Doctoral Scientists and Engineers in the United States* 1996) Since then, many of the core questions have remained the same, so year-to-year comparisons can be made among the 1993-2017 waves. The sample's included individuals may vary from year to year, as substantial changes have been made to the survey's target population. Starting in 2010, the SDR began to survey individuals who have moved abroad in the International SDR (or ISDR) rather than dropping them from the sample: for the 2010 and 2013 waves, the sample design accounts for individuals residing outside of the U.S. who received doctorate degrees since 2001; starting in 2015, all SED individuals were included in sampling - regardless of academic year of award or post-graduation residency. The 2015 wave also saw a major expansion of the SDR sample from approximately 47,000 individuals to 120,000 individuals. To accomplish that increase in sampling, a new sample was selected from the entire SED: the 2015 wave only includes 16,075 individuals from the 2013 SDR; the remainder was newly selected from the 2013-2015 SED.(Foley, 2015)

A limited selection of variables are available for public use and can be downloaded from the Scientists and Engineers Statistical Data System. For access to restricted use microdata, the NSF has a standardized licensed application with instructions available at https://www.nsf.gov/statistics/license/index.cfm. Note that the application now restricts to waves after the 1993 redesign; individuals seeking earlier SDR data may need to separately contact the NSF.

Given the extensive data collected and relative ease of obtaining a license, the SED and SDR are popular resources for researchers studying the careers of scientists. The first two chapters of this dissertation use the SED linked to the 1993-2015 waves of the SDR; STATA .do files used to perform these analyses are available at https://github.com/stephaniedcheng. Ginther and Kahn (2017) utilize the 1981-2013 waves of the SDR matched to the 1980-2013 SED to examine the impact starting in a postdoctoral position on the employment sector and salaries of biomedical Ph.Ds.; they estimate ex-postdoctoral researchers gave up 17-21% of their present value of income over the first fifteen years of their careers relative to Ph.Ds. with no postdoctoral experience. Lan (2012) uses the SED to examine the impact of increased permanent visas through the Chinese Student Protection Act of 1992 on postdoctoral participation; he finds that permanent visa holders are 24 percent less likely to take postdoctoral positions than temporary visa holders. Kahn and Macgarvie (2018) combine data from the 2010-2015 waves of the ISDR with country-based limits on EB-2 green cards to estimate the relationship between visa delays and stay rates of international doctorates; they find each year of visa delay leads to a 2.4 percentage point decline in Chinese graduate stay rates, while Indian graduate students are only affected by very long delays (those facing >5.5 years of delay have a 8.9

percentage point lower stay rate). Agarwal and Ohyama (2013) use the 1995-2006 SDR to fit a life cycle model of human capital investments sorting heterogeneous scientists into different career trajectories; they find evidence of sorting by ability for basic over applied academic research and sorting by non-monetary returns into academia over industry. Mishagina (2009) examines the occupational choices of science and engineering doctorates using the 1973-2001 SDR and 1957-2005 SED; she finds that while 72 peercent of doctorates start their careers in R&D tasks, only 45 percent were still in R&D thirty years later - with 80 percent of switchers moving into applied tasks.

3.2.2 Science & Engineering Ph.D. & Postdoctoral Survey (SEPPS)

Filling in gaps about science trainees' preferences, expectations, and abilities, Roach and Sauermann (2016) administer the Science & Engineering Ph.D. & Postdoctoral Survey (SEPPS) to follow nearly 6,000 Ph.D. candidates across 39 research-intensive universities and five major STEM fields in 2010, 2013, and 2016. SEPPS's longitudinal structure allows them to examine individuals from the early vs. late stages of their Ph.D. (as in Roach and Sauermann, 2017); from Ph.D. to postdoc (as in Roach and Sauermann, 2016); and a smaller sample from postdoc to postdoc. The survey covers a wide range of measures including career preferences; objective ability (e.g. number of publications, patents, and fellowships); subjective ability (e.g. self-reported research ability relative to peers); expectations about the job market (e.g. percent of field on tenure-track five years post-graduation, expected salary); expectations about one's own career (e.g. probability of being on tenure-track within five years); and reasons for pursuing postdoctoral positions. Of particular note is how the surveys shed light on non-academic and non-research careers: Roach and Sauermann (2014) find that over one third of Ph.D. candidates most likely to seek positions in industrial research are not willing to take a lower salary for the opportunity to publish, and Roach and Sauermann (2017) find that 20 percent of early Ph.Ds. are not interested in academic careers - rising to 45 percent of individuals later in their Ph.Ds. To shed more light on this matter, the surveys also include questions on Ph.D. and postdoctoral interest in industry careers and entrepreneurship. The authors have generously provided a public-use dataset; for further information on the survey, researchers should contact the authors directly.

3.2.3 National Postdoc Association (NPA) Survey

To better understand the institutional context, the National Postdoc Association (NPA) surveys the resources available to postdoctoral researchers at each member university. The NPA survey is distributed to postdoctoral offices at NPA's member institutions: 74 institutions completed the 2013 wave, 102 completed the 2016 wave, and 199 completed the 2019 wave. The survey asks about institutional and postdoctoral population demographics; structure of the institution's postdoctoral office; postdoctoral policies (e.g. term limits, exit survey practices); minimum postdoctoral stipend policies (in particular, whether institutions adopt the NIH recommended stipend scale - see Subsection 3.5.5); postdoctoral benefits (e.g. health insurance, maternity/paternity leave, retirement plans); and professional development/training offerings. The 2016 wave also overlapped with expected changes to the Fair Labor Standards Act (FLSA), which would have increased minimum postdoctoral stipends but was overturned shortly before implementation in December 2016. In response, the NPA sent a follow-up questionnaire in early 2017 to its member institutions to confirm if there were any changes to their responses on postdoctoral compensation. The survey results are detailed in the 2014, 2017, and 2021 NPA Institutional Policy Reports; researchers interested in the using the institution-level data should contact the NPA directly.(Ferguson, Huang, et al., 2014; Ferguson, McTighe, et al., 2017; Ferguson, Chen, and Costello, 2021) While these surveys do not survey individual postdoctoral researchers, this institution-level data could be merged with individual-level data to form a more complete picture of their postdoctoral appointments.

3.3 Snapshot Surveys

3.3.1 NSF Survey of Graduate Students and Postdoctorates in Science and Engineering (GSS)

The NSF Survey of Graduate Students and Postdoctorates in Science and Engineering (GSS) is an annual count of all research-based graduate students, postdoctoral appointees, and doctorate-level nonfaculty researchers at U.S. universities. Compared to the NSF SED and SDR, which focus on individuals who received their doctorates from U.S. institutions, this survey encompasses the significant proportion of individuals who received their STEM doctorates abroad but are working in the U.S.[48] The data is publicly available at https://www.nsf.gov/statistics/srvygradpostdoc/pub_data.cfm and can be used to assess general shifts in graduate enrollment and postdoctoral appointments.

[48] The 2005 Sigma Xi survey (see Subsection 3.3.3) estimates that 79 percent of foreign-born postdoctorates working in the U.S. received their doctorates outside of the U.S.(Davis, 2005)

The GSS does have several limitations: the survey is limited in scope to each university's tabulations by field of study, U.S. citizenship status, race/ethnicity, gender, part-time or full-time status, and largest mechanism of financial support. It does not include non-academic institutions such as research centers and federal agencies. Prior to 2017, the GSS did not distinguish between Master's and Ph.D. programs in counting graduate students. Because the GSS is distributed to academic institutions and not individuals, it is dependent on the academic institution keeping an accurate count of the number of researchers at their facilities. This is especially problematic in counting the number of postdoctoral appointees, which may be classified under different titles (e.g. "postdoc" vs. "fellow") at different universities; are transient in nature; and - particularly if postdoctoral hiring is handled solely by principal investigators - may not be consistently tracked by universities. In 2010, the GSS was redesigned to improve the accuracy of postdoctoral counts. However, there remain concerns that the GSS may still be underestimating the total number of postdoctoral researchers.(Einaudi, Heuer, and Green, 2013; Pickett, Bankston, and McDowell, 2017) With these caveats in mind, the data is one of the longest running surveys on the U.S. science trainees and thus gives a good sketch of long-term general trends in the scientific labor force.

3.3.2 Job Preferences: Stern (2004)

Stern (2004) surveys Ph.D. biologists who are completing a job search to determine their preferences for job characteristics - in particular, their willingness to trade off a higher salary for more science-oriented jobs. The survey contains five parts: 1) resume information about the respondent's background and demographics; 2) length and outcome of job search; 3) comparing job offers and an ordinal ranking of offers; 4) cardinal comparison (generally in magnitude and intensity of characteristics) of each individual offer; and 5) ranking of the importance of different job characteristics. The survey was distributed to current postdoctoral researchers whose funding was expiring at four U.S. research institutions; participants of two American Association for the Advancement of Science (AAAS)-sponsored Biology Job Fairs in Cambridge, MA and Palo Alto, CA; and post-Ph.D. biologists with resumes posted to www.biomednet.com. While the overall dataset consists of 107 biologists receiving a total of 223 job offers, the paper focuses on individuals who received multiple research job offers. 66 individuals had multiple job offers; this allows for applicant fixed effects, controlling for heterogeneity such as overall ability or attractiveness to employers. Eliminating non-research jobs such as management consulting or lab management gives more similar job comparisons, reducing the sample down to 164 job offers. Because some individuals only completed the ordinal or cardinal comparisons between jobs, the analysis separates into two samples: a cardinal sample of 121 job offers across 52 individuals and an ordinal sample of 134 job offers across 51 individuals. Using this reduced sample, Stern (2004) finds that a one standard deviation increase in "science index" - defined as a linear combination of the job's allowance for publishing in external journals, Likert scale rating of incentives to publish in refereed outside journals, and allowance for continuation of current postdoctoral research project - is associated with a more than six percent reduction in predicted wage. He does note that - relative to the variance associated with each of the measured job characteristics - the single-offer averages are not substantially different from the multiple-offer averages. Thus, it may be possible to utilize the remaining single-offer sample in further analysis.

3.3.3 Postdoctoral Experience: Sigma Xi, National Postdoc Survey (NPS)

One of the first major U.S. postdoctoral surveys, the 2005 Sigma Xi survey collects information on 7,600 postdoctoral researchers from 46 institutions, including eighteen of the top twenty academic employers and the National Institutes of Health (NIH).(Davis, 2005) The questionnaire asks respondents about their demographics (e.g. race, ethnicity, citizenship, location obtained doctorate, age, and family structure); postdoctoral satisfaction; salaries and benefits; career expectations; mentorship; and postdoctoral administration. Approximately one-third of the survey were considered "core" questions and asked of all respondents; to manage the time needed to fill out the survey, the remaining questions were randomly administered within each institution's participating population. These questions have been made available on the Sigma Xi website at http://postdoc.sigmaxi.org/questions. Due to a system issue, the raw survey data is unfortunately no longer available to researchers. While the Sigma Xi survey ultimately was a one-shot survey, its questionnaire can provide inspiration for future postdoctoral surveys. Researchers may find it helpful to examine Sigma Xi's extensive list of survey questions in designing their own postdoctoral surveys.

One of the surveys inspired by Sigma Xi, the National Postdoc Survey (NPS) is a postdoctoral survey "designed from a postdoc perspective." Created by postdoctoral researchers primarily associated with the University of Chicago, the 2016 inaugural survey contains responses from 7,603 primarily life science postdoctoral researchers at 351 U.S. institutions; a second wave wrapped up on December 31, 2019. Compared to previously mentioned postdoctoral surveys, the NPS focuses more on asking about the postdoc-PI relationship; availability of professional development programs; finances, benefits, and cost of living; and postdoc satisfaction. It also asks about demographics; grants and publications; job market perceptions and career plans (including back-up plans); and reasons for taking on postdoctoral positions. The results of the 2016 survey are documented in McConnell et al. (2018): they find that formal mentorship training is positively correlated with postdoctoral satisfaction and preference for mentor's career choice. The paper also goes into depth on the protocol and includes the survey instrument in their "Additional Files" section. Summary data for institutions, fields, and regions with more than fifty respondents are available upon request; researchers should contact the study authors for more information.

3.4 Experiments

3.4.1 NIH Broadening Experiences in Scientific Training (BEST)

In 2013, the NIH created the Director's Broadening Experiences in Scientific Training (BEST) program. Institutions awarded a five year BEST grant implement an experimental training opportunity to prepare biomedical graduate students and postdoctoral researchers for a variety of - particularly non-academic - career options. Ten awards were made in 2013, followed by another seven in 2014.(Lenzi et al., 2020) While each program is individualized to the institution, they primarily used a combination of the following tools: having trainees fill out Individual Development Plan (IDP); offering general skills and professional development workshops (e.g. leadership, communication); holding seminars geared towards specific career paths (e.g. entrepreneurship, pharma); outside mentorship; and short-term shadowing or internship experiences. Additionally, BEST encourages its institutions to track the career outcomes of their biomedical graduate students and postdoctoral researchers over time. (At least two institutions have published the results of such tracking: Wayne State University in Mathur, Cano, et al., 2018 and University of California San Francisco in Silva, Jarlais, et al., 2016.) Because most programs are open to all biomedical graduate students and postdoctoral researchers at the university, BEST program evaluations tend to take differences in pre- and post- program surveys or interviews and correlate with demographics (such as gender, race, GRE score, etc.).(Mathur, Chow, et al., 2018; Petrie et al., 2017) There are some possibilities for further rigorous causal estimation: for example, Emory and Georgia Tech's combined program uses a cohort model, which takes in 30 new Ph.D. and postdoctoral scientists a year and leaves the remainder as a possible control group. Programs offering internships also tend to offer differing levels of involvement from 1-day shadowing to 6-month internships, which may allow for the testing of exposure effects not yet calculated by the current evaluations.(Schnoes et al., 2018; Chatterjee et al., 2019). Future partnership with BEST institutions may result in further understanding of the causal impacts of these career training programs.

3.4.2 Hypothetical Choices: Ganguli and Gaulé (2018), Janger and Nowotny (2016)

At least two papers utilize hypothetical choice experiments to measure scientists' willingness to pay for certain job features such as remaining in academia. In their 2017 survey of 1,605 current chemistry doctoral students, Ganguli and Gaulé (2018) ask respondents to imagine they have multiple job offers and select the percent chance (out of 100) they would accept one offer over the other. To test the respondent's preference for academic positions, the three hypothetical job offers are 1) research scientist at industry firm; 2) postdoctoral researcher at top U.S. university; and 3) teaching-focused assistant professor. To test the respondent's preference for location, they ask respondents to choose between two postdoctoral job offers that differ in either a U.S. university or a foreign university. The authors find that the mean probability of choosing the industry option is approximately 50 percent for both U.S. and foreign students; of choosing the postdoctoral appointment is 10.2 percentage points higher for foreign students (33.0% vs. 22.8%); and of choosing the teaching assistant professorship is 9.3 percentage points higher for U.S. students (26.2% vs. 16.9%). They also find that foreign students on average have a 12.4 percentage point stronger preference for U.S. postdoctoral positions than foreign positions (60.5% vs. 48.1%). These trends hold even when controlling for graduate school, gender, marital status, enrollment year, and field of study.

Similarly, Janger and Nowotny (2016) utilize the hypothetical choice methodology in a large-scale survey of more than 10,000 European researchers across different career stages. Part of the EU-funded "Mobility of Researchers 2" (MORE2) project, the survey asks 3,790 early-stage researchers and 6,425 later-stage, independent researchers for their choice between 3 randomly allocated, academic jobs.(*Support for continued data collection and analysis concerning mobility patterns and career paths of researchers* 2013) The job choices vary in salaries and benefits; country quality of life relative to the country the respondent currently working; and job characteristics (e.g. time for own research, funding, and opportunities for career advancement). The authors find that at average wages, a $1,000 wage increase raises the probability of choosing a job offer by approximately 0.8 percentage points for early-stage researchers and 0.9 percentage points for later-stage researchers. Using the coefficients of a conditional logit regression, the authors calculate the willingness to pay for various job features: in particular, early-stage researchers are willing to pay $2,100 for each additional contract year; $18,659 for tenure possible contigent on performance and job availability; and $21,026 for tenure contingent purely on research performance.

3.5 Databases

3.5.1 IRIS UMETRICS

Hosted by the University of Michigan's Institute for Research on Innovation & Science (IRIS), the "Universities: Measuring the Impacts of Research on Innovation, Competitiveness, and Science" (UMETRICS) project collects administrative data from over 30 member universities to examine the social and economic impact of academic research.[49] The core files contain university-sponsored award and grant level data on project expenditures; direct employee wages; vendor purchases; and subaward transactions. Employee data can be linked to ProQuest dissertation data (see Subsection 3.5.4), publications, patents, NSF SED data (see Subsection 3.2.1), and Census earnings data.[50] Awards can be linked to their grants' original application data through partnerships with the NIH, NSF, and the US Department of Agriculture.

Since its inception in 2013, approximately 100 researchers have accessed the UMETRICS data. Among other projects, they have analyzed the earnings outcomes of Ph.D. recipients (Zolas et al., 2015); the gender differences in the training and career outcomes of graduate students (Buffington et al., 2016), the relationship between geographic proximity of vendors and university research expenditures (Goldschlag et al., 2019); and the impact of declining federal R&D funding on the organization of research groups (Funk et al., 2019). Researchers interested in using the UMETRICS data can apply through their online form at https://iris.isr.umich.edu/research-data/access/. Individuals affiliated with IRIS member institutions can access the data for free, while non-IRIS affiliated individuals are charged a non-refundable seat fee of $1,250 ($625 for students) annually. Approved projects can then access deidentified data through a secure virtual data enclave.

3.5.2 Coalition of Next Generation Life Sciences (CNGLS)

In December 2017, the Coalition of Next Generation Life Sciences (CNGLS) was founded with the goal of providing career transparency for life science trainees. Over fifty member institutions have pledged to publicly release data on the career outcomes of their life science Ph.Ds. and postdoctoral researchers such as the admissions and matriculation of Ph.D. students; median time-to-degree and completion data for Ph.D. programs; Ph.D. and postdoctoral demographics (e.g. gender, underrepresented minority status, and

[49] A full list of IRIS members can be found at https://iris.isr.umich.edu/iris-members-map/.

[50] Linkages with restricted Census data such as W-2 earnings require secure Census Research Data Center (RDC) access, which may require co-authoring with a current Census employee.

citizenship status); median time in postdoctoral positions at the institution; and Ph.D. and postdoctoral alumni careers. CNGLS provides member institutions reporting guidelines, which allows for cross-institution comparisons. Of particular note is work done by Silva, Mejía, and Watkins (2019) at the University of California San Francisco (UCSF): meta-researchers may find their paper a helpful blueprint for how to collect and categorize the career outcomes of Ph.D. and postdoctoral career outcomes. Member institutions host their data on their own websites, which is linked on the CNGLS website. Unfortunately, universities do not provide the raw data counts; instead, most provide data visualizations through Tableau graphs across multiple webpages. Thus, meta-researchers hoping to use data from CNGLS institutions may need to scrape the information off each individual institution website.

3.5.3 Grants: Research Portfolio Online Reporting Tools Expenditures & Results (RePORTER)

As part of the federal government's goals for public transparency and accountability, information on research projects funded by select agencies can be accessed through their online repository, the Research Portfolio Online Reporting Tools Expenditures and Results (RePORTER).[51] This system gives yearly funding success rates (defined as the percentage of reviewed grant applications that receive funding) and allows the general public to query for the projects, publications, patents, and clinical studies tied to each grant. Meta-researchers can also take advantage of downloading bulk RePORTER data through their ExPORTER system, which conveniently packages information on all funded projects in each fiscal year since 1985.[52] For each project, ExPORTER collects information on the principal investigators' names; project title and abstract; grant type; administering institute or center; budget start and end dates; grantee organization; and total cost (as well as divided into direct and indirect costs). It links to MEDLINE and PubMed publication data (see Subsection 3.5.4 for more detail; RePORTER data includes author list, journal information, and publication date); federal patent data (patent ID and title); and clinical studies (title, ClinicalTrials.gov ID, and current stage). Publication data is refreshed every year; patents and clinical studies data are refreshed every week.

Thus far, the RePORTER data has been extensively used to examine the relationship between research funding and outputs: for example, how targeted grant opportunities can shift scientists' research direction (Myers, 2019); how interruptions in grant funding affect scientists' research activity (Tham, 2019); and the

[51] This is primarily the NIH, but the system also includes grants funded by the Administration for Children and Families (ACF), Agency for Healthcare Research and Quality (AHRQ), Centers for Disease Control and Prevention (CDC), Health Resources and Services Administration (HRSA), U.S. Food and Drug Administration (FDA), and Veterans Affairs (VA).

[52] Additionally, ExPORTER's predecessor, CRISP, contains project data from FY1970-2009. However, CRISP data is not linked to publications, patents, or clinical studies data.

direct and indirect channels through which federal funding affects patenting (Li, Azoulay, and Sampat, 2017). In order to study the impact of federal funding on the careers of established scientists, RePORTER data at the principal investigator level could feasibly be linked to CVs and other career outcomes. For example, Azoulay, Ganguli, and Zivin (2017) pull together an extensive number of data sources including RePORTER data to follow 10,051 elite life scientists over time; they find that scientists who've recently received NIH funding are less likely to move, which they attribute to the high transaction costs of transferring funds between institutions. To study the impact on science trainees would be more time-intensive, as only the principal investigators' are listed on RePORTER's project information. However, it may be possible to do so by linking principal investigators to their lab employees at the time of funding or by identifying trainees from linked publication data.

For projects outside of U.S.-funded life sciences, a Federal RePORTER and a World RePORT system have been established. Since fiscal year 2000, the Federal RePORTER annually collects funding data from the Department of Defense (DOD), Department of Education (DOE), Environmental Portection Agency (EPA), Department of Health and Human Services (HHS), National Aeronautics and Space Administration (NASA), and National Science Foundation (NSF). Publications are linked to project data from the EPA; NSF; and select HHS, DOD, and USDA departments. Thus far, Federal RePORTER data is not linked to patents data. Since fiscal year 2012, the World RePORT highlights biomedical research investments from some of the world's largest funding organizations: it currently includes the Bill & Melinda Gates Foundation, the Canadian Institutes of Health Research, European Commission, European & Developing Countries Clinical Trials Partnership, Medical Research Council, Institut Pasteur, Swedish International Development Cooperation Agency, Swedish Research Council, and Wellcome Trust. However, the World RePORT currently does not link projects funded by these organizations to their publications or patents. While these two online repositories are limited compared to the NIH RePORTER, their future expansions may allow for more extensive study of especially non-biomedical and non-U.S. research.

3.5.4 Publications & Citations: ProQuest, MEDLINE/PubMed, ORCID, Scopus, Web of Science

Several online databases provide information on scientific publications and their citation history. They are generally used to search a scientist's publication record: one queries with the scientist's name, affiliation, and field of study, then the database returns a list of publication names, abstracts, journal information, links to the full text, and yearly citations. Some databases may also allow searches for a scientist's clinical trials, conference proceedings, and patents.

The most commonly used databases include ProQuest, MEDLINE/PubMed, ORCID, Scopus, and Web of Science. The ProQuest Dissertations and Theses database is the largest repository of primarily U.S. graduate dissertations and theses, containing over 4 million theses from over 3,000 universities. Each year, more than 130,000 works are added to the database. In addition to the full-texts (primarily for theses from 1997 onward), ProQuest includes metadata such as the author name, advisor name, committee members, department, university, publication year, and degree date.

For biomedical meta-research, the premiere database is MEDLINE/PubMed: MEDLINE is the National Library of Medicine's journal citation database and contains over 26 million references to biomedical publications from more than 5,200 journals since 1946; it is primarily accessed through the freely available PubMed, which includes additional citation databases for more than 30 million references. For fields beyond biomedical research, Scopus and Web of Science are two subscription-based services that cover a wide variety of academic fields. Scopus contains approximately 1.4 billion citations from more than 24,600 journals and 5,000 publishers since 1970; it also automatically constructs approximately 16 million author profiles. Web of Science contains approximately 1.7 billion citations from over 21,100 high-impact journals since 1900. In comparison to Scopus, Web of Science focuses on "high influence" publications and covers fewer non-U.S. and interdisciplinary research. Most researchers will obtain access through their academic institutions, which typically subscribes to one of the two.

One drawback of these online databases is the possibility of mismatch between authors and publications due to common names. To correct for this, ORCID is an online database that provides scientists with a persistent digital identifier that they can connect to their affiliations, grants, publications, etc. Because researchers must register for an identifier and link to their work themselves, ORCID is smaller than the other databases mentioned. Its advantage as its network grows is that it provides complete publication work with less possibility of mismatch.

On their own, publication and citation data are limited in their research usability. They are generally combined with additional scientist information as proxies for scientific ability or productivity. For example, MEDLINE/PubMed is the source from which RePORTER (see Subsection 3.5.3) links funding to publication data. Ross et al. (2019) measure how research quality, as proxied by the number of citations and publications, declines over a scientist's career. Conti and Visentin (2015) uses Scopus publication data to determine the within-field research ranking of universities; the R&D intensiveness of companies; and the research quality of trainees and their supervisors . Balsmeier and Pellens (2014) counts cumulative number of publications in the Web of Science database as a proxy for scientist productivity, finding that having an additional publication decreases a scientist's propensity to leave academe by 6 percent.

3.5.5 Stipends: NIH Guidelines, Future of Research, PhDStipends.com, & PostdocSalaries.com

Meta-researchers may be interested in looking at Ph.D. and postdoctoral stipends, especially as science advocacy groups argue low stipends disincentivize talented individuals from remaining in STEM research. For the biomedical fields, a good starting point is the NIH Ruth L. Kirschstein National Research Service Award (NRSA) postdoctoral stipend guidelines. These give the NIH recommended stipend amount for a postdoctoral researcher with a certain number of years of experience at the institution. The NIH has published their historical stipend guidelines on their website and releases an announcement of annual stipend amounts each year.(*Kirschstein-NRSA Stipend History* 2016, *Ruth L. Kirschstein National Research Service Award (NRSA) Stipends, Tuition/Fees and Other Budgetary Levels Effective for Fiscal Year 2020* 2020). Deemed the "gold standard" for minimum stipend amounts, many institutions peg their postdoctoral stipends to the NIH guidelines even for researchers not funded by the NIH.(Ferguson, McTighe, et al., 2017) The NPA's Institutional Policy Reports (see Subsection 3.2.3) estimate that approximately half of their member institutions set minimum postdoctoral stipends to the NIH NRSA amount between 2013-2019.(Ferguson, Huang, et al., 2014, Ferguson, Chen, and Costello, 2021) This trend continued even when the stipend guideline increased significantly in 2016, with 61 percent of NPA member institutions continuing to peg their postdoctoral stipends to the NIH NRSA amount.(Ferguson, McTighe, et al., 2017)

Several grassroots advocacy groups have also collected information on science trainee stipends to improve transparency. In 2016, Boston-based Future of Research submitted Freedom of Information Act (FOIA) requests to U.S. public institutions with at least 300 postdoctoral researchers, obtaining the salaries and job titles for over 13,000 postdoctoral researchers at 52 public U.S. institutions; the private university Boston University also contributed stipend data. They find that 22.7% of postdoctoral researchers had salaries within $25 of the NIH NRSA minimum stipend of $47,484 and 61.0% of postdoctoral researchers having stipends between $40,000-$49,999.99.(Athanasiadou. et al., 2017) The group also publicly provides the de-identified, individual-level data on job title, university, and stipend on their website at https://www.futureofresearch.org/investigating-postdoc-salaries/.

Because Future of Research's dataset is mostly limited to postdoctoral researchers at public institutions, they encourage Ph.D. and postdoctoral researchers to anonymously submit their historical and current stipend information to PhDStipends.com and PostdocSalaries.com, which both publicly display the results of submitted stipend information on their websites. PhDStipends.com has over 8,000 submissions that give university; department; overall pay; living wage ratio (measured using the Poverty in America Living Wage Calculator for a single person with no dependents); academic year; program year; and any additional comments. PostdocSalaries.com has over 1,500 submissions that give institution; department; title; salary;

living wage ratio; benefits; whether this is a negotiated offer; academic year; years since Ph.D.; whether the institution continues the postdoctoral researcher an employee; and any additional comments.

3.5.6 Academic Family Tree

Several efforts have been made to link STEM trainees to their mentors, creating an academic genealogy of researchers. The largest, Academic Family Tree, started with neuroscience in January 2005 and has since expanded to approximately 748,100 people across over sixty fields of study.[53] This open-source database links scientists from mentor to mentee in a "family tree" structure, with start and end dates of training for each mentee. It also connects to their publication history through the PubMed database and to their NIH and NSF funding data through the Federal RePORTER (Star Metrics) system.[54] Using the Academic Family Tree, Liénard et al. (2018) examine the impact of graduate and postdoctoral mentorship by examining 18,856 "triples" of researchers - consisting of a trainee, a graduate mentor, and a postdoctoral mentor; they find that the postdoctoral mentor has a larger influence than the graduate mentor on a trainee's odds of continuing in academia and own training of new scientists.

There are a few caveats with using the Academic Family Tree for further research. Because the Academic Family Tree is open-source, it depends on user inputs to identify mentor-mentee relationships and thus is not a universal representation of academic relationships. The trees also tend to focus on academic research relationships, so STEM trainees who leave academia or are no longer doing academic research are less likely to be in this database. As the number of Academic Family Tree contributors grows, it may be able to provide a more complete picture of mentor-mentee relationships.

3.5.7 Diverse Scientists: Request a Woman in STEMM, CAISE

For researchers studying diversity in STEM, there are several databases listing female and minority scientists. Originally created to encourage more diversity in seminar speakers and journalism quotes, meta-researchers could potentially draw from these databases to create scientist samples. The Database of Databases of Diverse Speakers in STEM acts a starting point, compiling a list of databases that collect information on underrepresented groups in STEM. Each database may focus on a different subset of research fields and

[53] They have linked to other Academic Family Tree projects in their F.A.Q., such as the Mathematics Genealogy Project, the Family Tree of Trade Economists, and Brown University's planetary geology family tree.

[54] As PubMed and RePORTER primarily focuses on biomedical fields, these scientists are more likely to list publication and funding data on the Academic Family Tree website.

included groups. For example, the Gage (formerly "Request a Woman Scientist") database consists of over 7,500 women and gender minoritiees from 174 scientific disciplines and 133 countries.(McCullagh et al., 2019) Women in science, technology, engineering, mathematics, and medicine (STEMM) can provide their contact information, career stage, degree, scientific discipline, geographic location, self-identifying dimensions of representation, and professional availability (i.e. willingness to be a seminar speaker, speak to a journalist, etc.). Similarly, the Counting All for Inclusion in STEM Equity (CAISE) database collects information on historically marginalized individuals (HMI) with terminal STEM degrees who are currently conducting research at an academic institution. This includes their contact information, HMI identifiers, field of study, a link to their professional website, and professional availability. Given that the nature of these databases to bring awareness to and more easily contact underrepresented groups in STEM, the listed individuals may be willing to contribute to surveys - particularly on diversity in STEM - or can provide a starting sample of scientists to merge onto other datasets such as their publications, patents, and career paths.

3.5.8 Professional Associations

In addition to the data sources that have already been mentioned in this white paper, consider partnerships with science advocacy groups, professional associations, and honor societies to generate new data on the careers of scientists. Among many others, this includes the American Association of Arts and Sciences (AAAS), American Society for Biochemistry and Molecular Biology (ASBMB), American Chemical Society (ACS), engineering honor society Tau Beta Pi (TBP), and American Physics Society (APS). Not only can they provide first-hand knowledge about the types of careers pursued in their field, these organizations may have existing career programs that could be leveraged in meta-research experiments. For example, APS offers an industry mentorship program that matches physics graduate students and postdoctoral researchers with physicists who have experience working in industry. Professional associations can also assist in constructing a large sample of STEM trainees. As they maintain contact information for working professionals in their field, they can help meta-researchers distribute surveys or administer other data collection processes to their membership. For example, Sigma Xi and the National Postdoc Survey (see Subsection 3.3.3) have distributed their survey through the National Postdoctoral Association (see Subection 3.2.3) and by contacting individual institutions' postdoctoral offices. Especially if meta-researchers are interested in a particular field, professional associations are a good starting point to examine what career projects have already been implemented and to contact a large group of professionals in the field.

3.6 Future Avenues

This white paper has outlined existing sources for studying the long-term career paths of scientists, though each come with their limitations. The majority of surveys focus on individuals in the biomedical sciences who received their Ph.Ds. from U.S. institutions; much is left to be learned about the estimated 71 percent of STEM Ph.Ds. in other fields and 47 percent of STEM postdoctoral researchers working in the U.S. who received their degrees abroad.(Davis, 2005) Several databases can indirectly shed light on the career paths of scientists by piecing together data from federal grants (see Subsection 3.5.3), publications (see Subection 3.5.4), and mentorship (see Subection 3.5.6). For a subset of schools, organizations have already begun the work of merging these various databases together; in particular, UMETRICS (see Subsection 3.5.1) is working on combining lab-level employee data with grants, publications, patents, and Census earnings data. However, more work is needed to construct a nationally representative sample of STEM trainees with complete career paths, ability proxies, and preference measures. Future partnerships with science advocacy and professional associations may assist with constructing such a data sample. While such an endeavor will take a considerable amount of work, it would open many more opportunities to study the long-term careers of scientists.

Appendices

A Tracking STEM Ph.D. Careers

A.1 Career Paths Construction

This appendix details the methodology used to identify a SED-SDR individual's career paths across six job types and two employment statuses. It performs the methodology on the example Ph.D. whose true career path is given in Appendix Table A.1. Based on this true path, the individual fills out the job-related variables from each SED or SDR survey in Appendix Table A.2. Note that this data has been constructed for example purposes and does not represent an actual individual in the SED-SDR data.

Table A.1: Example Individual's True Career Path

refyr (1)	*PD* (2)	*TT* (3)	*NT* (4)	*ID* (5)	*NP* (6)	*GV* (7)	*UN* (8)	*NL* (9)
1990	X							
1991	Y							
1992	Y							
1993	Y							
1994		X						
1995		X						
1996		X						
1997		X						
1998		X						
1999			X					
2000			X		X			
2001					X			
2002				X				
2003				X				
2004				Y				
2005				Y				
2006				Y				
2007							X	
2008						X		
2009						Y		
2010						Y		
2011						Y		
2012						Y		X
2013								X
2014						X		
2015						X		

Notes: This table gives the true career path of a constructed SDR individual. Column 1 gives the reference year, *refyr*. Columns 2-9 give job types and employment statuses abbreviated as postdoctoral researcher (PD), academic tenure-track (TT), academic non-tenure track (NT), for-profit industry (ID), non-profit (NP), government (GV), unemployed (UN), and not in labor force (NL). A marked box denotes employment in that job type or employment status in that year; if an individual switches jobs but remains in the same job type, different jobs are denoted by switching the markings (X, Y, etc.). For example, the individual switches from one postdoctoral position to another in 1991, so the first postdoctoral job is denoted by X and the second is denoted by Y.

Table A.2: Example Individual's Responses to SED/SDR

Survey (1)	*refyr* (2)	*phdcy* (3)	*pdocstat* (4)	*pdocplan* (5)	*strtyr* (6)	*pdix* (7)	*lfstat* (8)	*emsecdt* (9)	*facten* (10)	*tensta* (11)	*emsmi* (12)	*lwyr* (13)	*pd1syr* (14)	*pd1eyr* (15)	*pd2syr* (16)	*pd2eyr* (17)
SED	1990	1990	2	0												
SDR	1993	1990			1991	1	1	11	4	5						
SDR	1995	1990			1994	0	1	11	1	4	4		1991	1993	1990	1990
SDR	1997	1990			1994	0	1	11	1	4	1					
SDR	1999	1991			1999	0	1	11	4	5	4					
SDR	2001	1990			2000	0	1	23			4					
SDR	2003	1990			2002	0	1	22			4					
SDR	2006	1990			2004	0	1	21			3		1991	1993	1990	1990
SDR	2008	1990			2008	0	1	32			4					
SDR	2010	1990			2008	0	1	32			2					
SDR	2013	1990				0	3					2012				
SDR	2015	1990			2014	0	1	32								

Notes: This table gives the constructed SDR individual's responses to the SED and the 1993-2015 SDR waves, based on their true career path in Table A.1. Column 1 gives the survey type (SED or SDR). Column 2 gives the reference year for the survey, *refyr*. Column 3 reports the Ph.D. graduation calendar year, *phdcy*; note that there is a typo in the 1999 SDR response. Columns 4-5 gives the individual's post-graduation status, *pdocstat*, and post-graduation planned employment, *pdocplan*, reported in the SED. Column 6 gives the starting year, *strtyr*, for the reported principal job. Column 7 is an indicator for whether the principal job is a postdoctoral position, *pdix*. Column 8 gives the labor force status, *lfstat*. Column 9 gives the employment sector, *emsecdt*. Columns 10-11 describe the faculty rank, *facten*, and tenure status, *tensta*, for employment in academic institutions. Column 12 describes whether the individual held the same job and/or employer during the last survey, *emsmi*. Column 13 gives the last year worked if unemployed or out of the labor force, *lwyr*. Columns 14-17 give retrospective start and end dates for the two most recent postdoctoral positions, *pd1syr-pd2eyr*; in this example individual, they did not have a third postdoctoral position, so *pd3syr* and *pd3eyr* are empty for all surveys.

I start by identifying all individuals covered by the 1993-2015 SDR, matching to their SED responses using the variable *refid,* and using their first weight observation *wtsurvy.* For demographics that don't vary over time – race, gender, birth date, birthplace, native US citizenship, educational attainment prior to the Ph.D. (including years out of school), Ph.D. field of study, Ph.D. institution, and Ph.D. graduation year – I consider the individuals' SED responses to be the definitive source for these variables. I calculate the number of years each individual spends in graduate school by taking the difference between the year an individual receives their Ph.D. and the year they receive their Bachelor's degree, subtracting any time they spend out of school.

I identify six possible principal job types individuals can hold:

- **Postdoctoral Researcher (PD):** In the SED, the individual's postgraduation plans (given by the variable *pdocplan*) are a postdoctoral fellowship, a postdoctoral research associateship, a traineeship, or a clinical residency internship. In the SDR, the indicator for a postdoctoral principal job, *pdix*, equals one; alternatively, in the 1995 or 2006 SDR, the individual identifies this time period as a postdoctoral position through the retrospective questions on postdoctoral history (given by postdoctoral starting and ending years, *pd*syr* and *pd*eyr).*

- **Academic Tenure-Track (TT):** In the SED, the individual's postgraduation plan is not a postdoctoral position (as defined above) but is employment in a U.S. 4-year college or university, medical school, research institute, or university hospital. In the SDR, the individual is not in a postdoctoral position but is either tenured or on the tenure track (as given by the variables *facten* and *tensta*).

- **Academic Non-Tenure Track (NT):** In the SED, the individual's postgraduation plan is not a postdoctoral or tenure-track academic (as defined above) but is employment in a U.S. community college, U.S K-12, or a foreign educational institution. In the SDR, the individual is not in a postdoctoral or tenure-track academic position but is employed in an educational institution (as given by the employment sector variable *emsecdt*).

- **Industry (ID):** For both the SED and SDR, the individual is employed in the for-profit industry sector, for-profit business sector, or is self-employed.

- **Non-Profit (NP):** In the SED, the individual's postgraduation plan is a not-for-profit organization or international organization such as UN, UNESCO, or WHO. In the SDR, the individual is employed in a non-profit sector.

- **Government (GV):** In the SED, the individual's postgraduation plan is employment at a foreign government, U.S. federal government, U.S. state government, or U.S. local government. In the SDR, the individual is employed in the government sector.

I also examine if individuals are not employed and hold the following non-employed statuses:

- **Unemployed (UN):** There is no information on unemployment in the SED. In the SDR, an individual's labor force status is unemployed (as given by the variable *lfstat)*.
- **Not in Labor Force (NL):** In the SED, the individual's postgraduation status is not seeking employment (including being a housewife, writing a book, or no employment). In the SDR, the individual's labor force status is not in the labor force.

To construct the career paths, I modify Ginther and Kahn (2017)'s methodology for measuring postdoctoral incidence over time to expand to different employment sectors. From the SED, I identify STEM Ph.Ds.' immediate post-graduation status using the variables *pdocstat*. Individuals are considered to be in a particular job type the year of their graduation if they indicated they are returning to employment, have a signed contract, or are in negotiations for that job type. From the SDR, I utilize variables on their current job,[55] comparison to their previous job,[56] and retrospective postdoctoral experience asked of respondents in 1995 and 2006.[57] Because some variables impart more information about one's job type than others, I use the following hierarchy to fill in indicators for each job type in each year from 1945-2015:

1. **New job:** Individual is starting a new job (given by start date) in that year. In the case of unemployed or out of labor force, the last year worked was the previous year.
2. **Postdoctoral retrospective:** Individual stated they were in a postdoctoral position in the retrospective 1995 and 2006 data, as given by the postdoctoral start and end dates. Fill indicators for all

[55]Current job variables include *pdix* (indicator for postdoctoral principal job), *facten* (faculty rank and tenure status), *tensta* (tenure status), *emsecdt* (employer sector), and *lfstat* (labor force status).

[56]The variable *emsmi* asks if individual holds the same employer and/or same job as the last SDR survey, typically two to three years earlier.

[57]The 1995 and 2006 waves of the SDR included an additional module on retrospective postdoctoral employment. Individuals in the SDR sample for the 1995 and 2006 waves were asked how many postdoctoral appointments they had held; the start and end dates for their three most recent postdoctoral appointments; and their reasons for pursuing postdoctoral appointments. For this purposes of constructing career paths, I utilize start and end years for the three most recent postdoctoral appointments (given by *pd*syr* and *pd*eyr*).

years between the start and end years.

3. **Current job:** Individual is currently in this job type; fill indicators for all years up through starting year. In the case of unemployed or out of labor force, fill indicators for all years just up to the year last worked.

4. **In same job type last survey:** Individual states they were either 1) in the same job and same employer, 2) in the same job but had a different employer, or 3) had the same employer but different job as the last survey. Denote these as case 4, case 4.1, and case 4.2 respectively. Fill indicators for current job type up to last survey year.

5. **Expected post-graduation job:** Fill in job type for an individual's graduation year from their expected post-graduation job type, as given by the SED.

6. **No other information, expected transition:** If steps 1-5 have not given any information on an individual's job type in a particular year but have given information in the previous year, assume that individuals were in the same job type as the year had information.

7. **No information expected:** For years before completing the Ph.D. and after the last year surveyed, the individual contributes no further information about their job type, so replace indicators with missing.

The example individual's indicators are given in Appendix Table A.3. I consider the highest step in the hierarchy as the most accurate representation of whether an individual was in that job type in that year.

Table A.3: Example Constructed Career Path

refyr (1)	*PD* (2)	*TT* (3)	*NT* (4)	*ID* (5)	*NP* (6)	*GV* (7)	*UN* (8)	*NL* (9)
1990	5, **2**							
1991	**1**, 2							
1992	3, **2**							
1993	3, **2**							
1994		**1**						
1995		**3**, 4						
1996		**3**, 4						
1997		**3**, 4						
1998		**6**						
1999			**1**					
2000			{}		**1**			
2001					**3**			
2002				**1**				
2003				**3**, 4.1				
2004				**1**, 4.1				
2005				**3**, 4.1				
2006				**3**, 4.1				
2007				{**6**}			{}	
2008						**1**, 4.2		
2009						**3**, 4.2		
2010						**3**, 4.2		
2011						**6**		
2012						{}		**1**
2013								**3**
2014						**1**		
2015						3		

Notes: This table gives the constructed career path based off survey responses in Table A.2. Column 1 gives the reference year, *refyr*. Columns 2-9 give job types and employment statuses abbreviated as postdoctoral researcher (PD), academic tenure-track (TT), academic non-tenure track (NT), for-profit industry (ID), non-profit (NP), government (GV), unemployed (UN), and not in labor force (NL). Boxes are marked with the steps of the hierarchy that the year satisfies: 1 denotes a new job; 2 denotes a postdoctoral position given by the retrospective module; 3 denotes a current job reaching back to its starting year; 4 denotes the same job and employer as the previous wave; 4.1 denotes the same job but different employer as the previous wave; 4.2 denotes the same employer but different job as the previous wave; 5 denotes the SED post-graduation plans; and 6 denotes an expected transition. The smallest number in each cell is bolded and used as the most accurate representation of whether the individual was in that job type in that year. Brackets denote differences from the true career path given in Table A.1.

Appendix Table A.4 gives the percent of indicators determined by each step. To estimate the number of years an individual is in a particular job type, I count one year for each year an indicator's most definitive step is steps 1-5 and a half year for each year an indicator's most definitive step is step 6. Transitions are defined by the new job type within two years of the last year spent in a different job type. As shown in Appendix Table A.3, the example individual is considered to have spent four years in a postdoctoral position, four and a half years in academic tenure-track, one year in non-tenure track, two years in non-profit, five and a half years in industry, two years not in labor force, and five and a half years in government. They have switched from postdoctoral to tenure track, tenure track to non-tenure track, non-tenure track to non-profit, non-profit to industry, industry to government, and not in labor force to government.

Table A.4: Percent of Job Indicators Determined by Step Hierarchy, STEM Sample

Step	PD (1)	TT (2)	NT (3)	ID (4)	GV (5)	NP (6)	UN (7)	NL (8)
1: New Job	21.8%	7.7%	13.3%	12.9%	10.1%	11.8%	32.8%	15.6%
2: Postdoc Retrospective	32.0%							
3: Current Job	15.4%	86.0%	80.2%	78.6%	79.2%	76.1%	64.2%	83.7%
4: Same Job, Same Employer	0.2%	0.2%	0.7%	0.3%	0.3%	0.3%		
4.1: Same Job, Diff Employer	0.8%	0.4%	1.0%	1.1%	0.6%	1.2%		
4.2: Diff Job, Same Employer	1.4%	2.1%	2.1%	2.8%	2.7%	2.3%		
5: Expected Post-Grad Job	18.7%	2.8%	1.4%	2.4%	5.0%	6.1%		
6: No Info, Expect Transition	9.6%	1.0%	1.3%	2.0%	2.1%	2.3%	3.1%	0.7%
Total # Obs	144,296	514,238	176,576	503,858	155,971	86,002	14,894	129,310

Notes: This table gives the percentage of job type indicators for STEM doctorate holders that are determined by each step in the described hierarchy: 1 denotes a new job; 2 denotes a postdoctoral position given by the retrospective module; 3 denotes a current job reaching back to its starting year; 4 denotes the same job and employer as the previous wave; 4.1 denotes the same job but different employer as the previous wave; 4.2 denotes the same employer but different job as the previous wave; 5 denotes the SED post-graduation plans; and 6 denotes an expected transition. Each column gives a different job type or employment status: 1) PD: postdoctoral researcher, 2) TT: academic tenure-track, 3) NT: non-tenure track, 4) ID: for-profit industry, 5) GV: government, 6) NP: non-profit, 7) UN: unemployed, and 8) NL: not in labor force.

This methodology is able to capture the majority of the true career path; however, the example also illustrates limitations when individuals switch principal jobs between survey years or have employment gaps for a year or less. The 1999-2000 non-tenure track and the 2009-2012 government positions are underestimated, as the individual switched to a different job type in a non-survey year. The 2007 unemployment gap is missed due to being in a non-survey year. The 2004-2006 for-profit job is overestimated due to a lack of job type information in 2007. Since transitions are defined by the last time an individual is observed in a job type, this methodology also misses the transition from government to not in labor force (as the individual returns to government later on).

A.2 Individual and Job Characteristic Interpolation

Once I have constructed the full career path, I pull additional information on worker and job characteristics from the SDR data. I calculate age as the difference between the birth year given in the SED and the year of interest. I construct indicators for marital status; any children living in the household; US native citizen; and US naturalized citizen. I fill in between SDR survey years by assuming that if individuals have not changed their status for consecutive survey years, they kept that status. If they have changed status, I fill in the intervening year indicators with 0.25/0.75 to denote a transition a negative/positive transition respectively.[58] Between the SED and SDR years, I fill in the US naturalized citizenship indicator only if it does not change between the SED and their first SDR survey year; no other interpolation is done between the SED and SDR.

For job characteristics over time, the variables of interest include salary, work activity indicators, occupational codes, federal support indicators, location, educational institution (if in academic position), tenure status (if in academic position), hours worked, indicator for full-time principal job, employer size, job benefits, and indicator for new business. Raw salaries have been converted to 2015 dollars using the CPI-U. If an individual is at a U.S. educational institution, I match to their institution's Carnegie Classification in that year. Occupational codes are matched to Ph.D. field of study using the key provided in Appendix Table A.5. For interpolation between survey years, I utilize the job indicators constructed in Appendix A.1 to determine years in the same job. For the same job, I assume that job field of work, occupation, location, educational institution (if in academic position) do not change and fill those characteristics in non-survey years. If a specific job is considered a new business, I allow this distinction for 5 years after the first time the individual first lists it as such. I do not interpolate other job characteristics across survey years.

[58] 3.6% of observations change marital status; 7.1% change having children living with them; and less than 1% change US citzenship or residency status between surveys.

Table A.5: NSF Occupational Codes Matched to Ph.D. Field of Study

Ph.D. General Field of Study	Occupational Codes
Agricultural Sciences/Natural Resources	210000-219999, 282710
Biological/Biomedical Sciences	220000-229999, 282730
Chemistry	310000-319999, 382750
Computer & Information Sciences	110000-119999
Economics	412320, 482780
Education	632530-632540, 732510-742990
Engineering	510000-579999, 582800
Health Sciences	610000-611140, 612870
Mathematics	120000-129999, 182760, 182860
Physics	330000-339999, 382890
Professional Fields	711410-721530, 781200
Psychology	432360, 482910
Other Physical Sciences	320000-329999, 341980
Other Social Sciences	420000-452380, 482900-482980

Notes: This table matches NSF occupational codes to the closest Ph.D. general field of study. Note that postsecondary teachers are matched to their field of study (e.g. mathematics teacher is counted in mathematics), not education. Labels for NSF occupational codes are given at https://ncses.nsf.gov/pubs/nsf21320/table/A-2.

B Trends Across STEM Fields

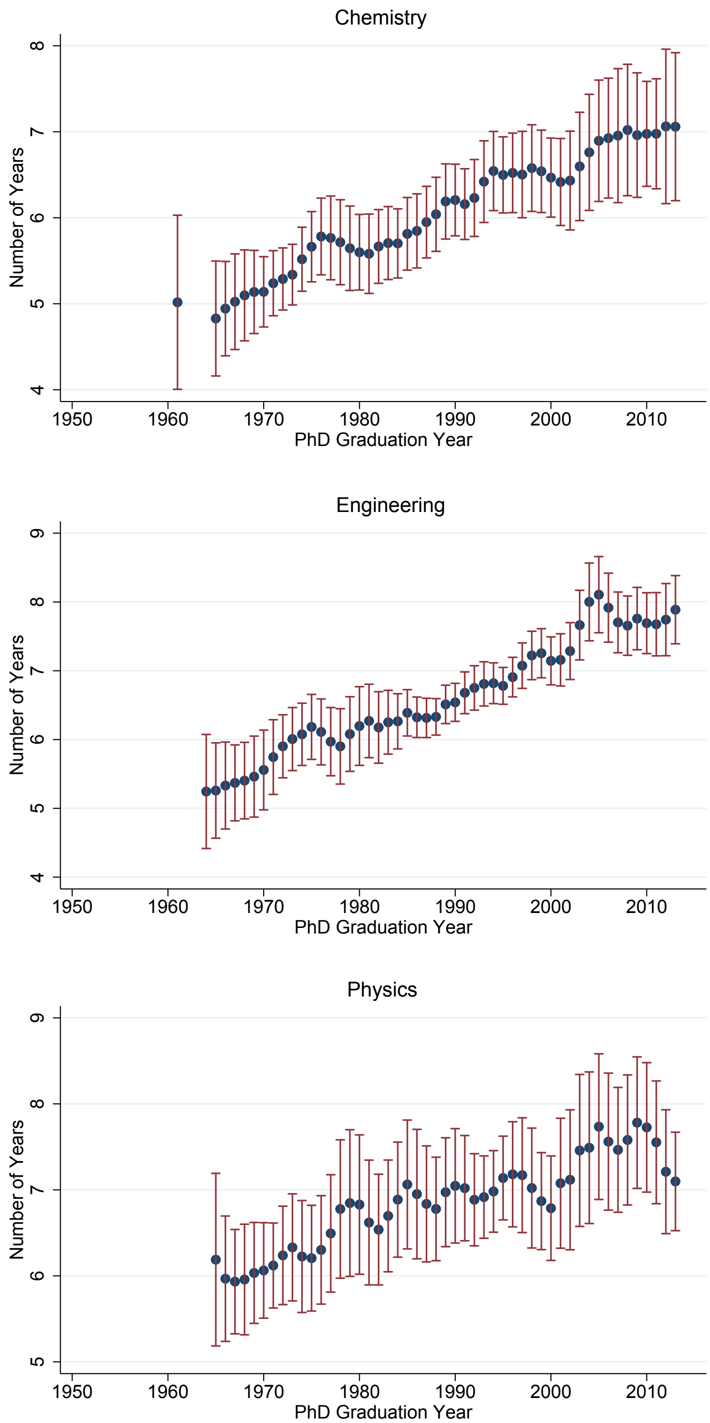


Figure B.1: Mean Years in Graduate School by Ph.D. Cohort for Additional Fields

Notes: These graphs give the three-year moving 95% confidence intervals for the mean years chemistry (top), engineering (middle), and physics (bottom) Ph.Ds. spend in graduate school, defined as Ph.D. graduation year minus Bachelor's graduation year and time spent out of school during these years, for each Ph.D. graduation cohort. For disclosure purposes, only cohorts with at least fifty individuals are shown.

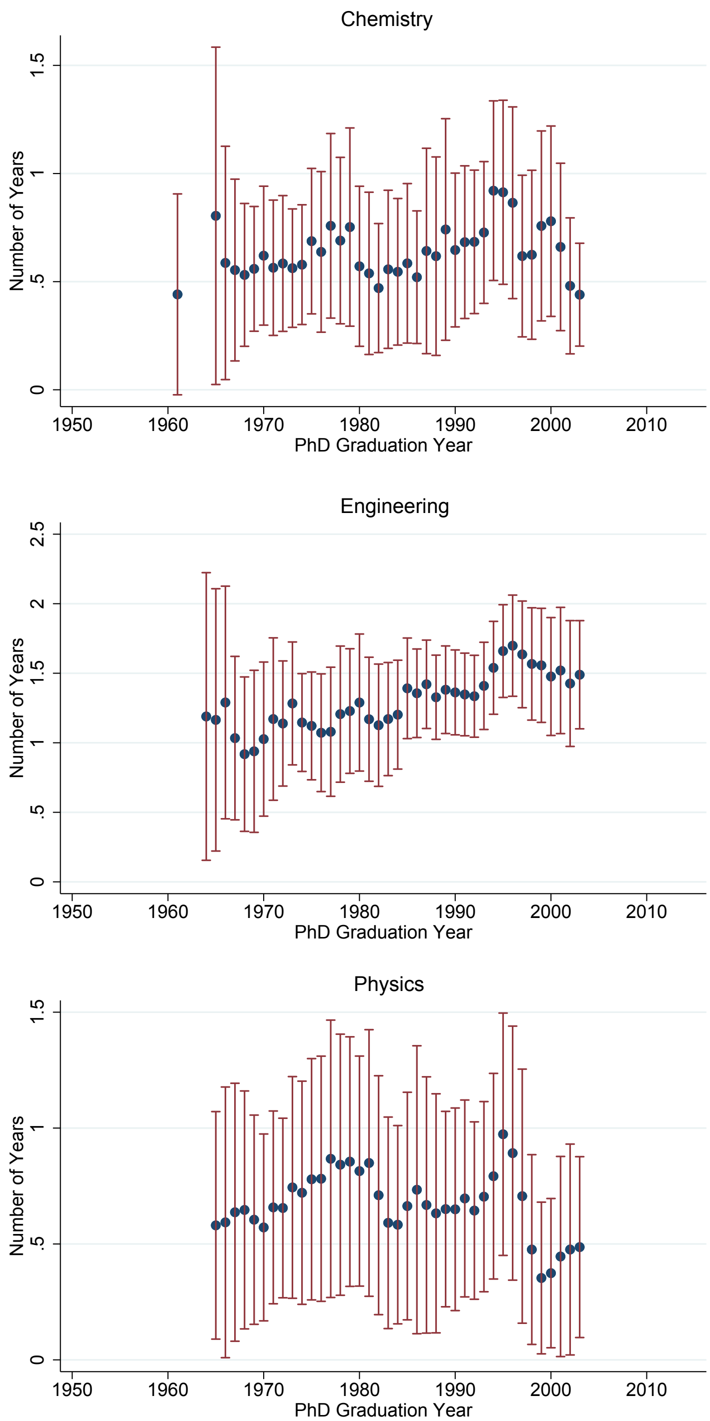


Figure B.2: Mean Time Out of Graduate School by Ph.D. Cohort for Additional Fields

Notes: These graphs give the three-year moving 95% confidence intervals for the mean time out between Bachelor's and Ph.D. graduation years for chemistry (top), engineering (middle), and physics (bottom) Ph.Ds. For disclosure purposes, only cohorts with at least fifty individuals are shown.

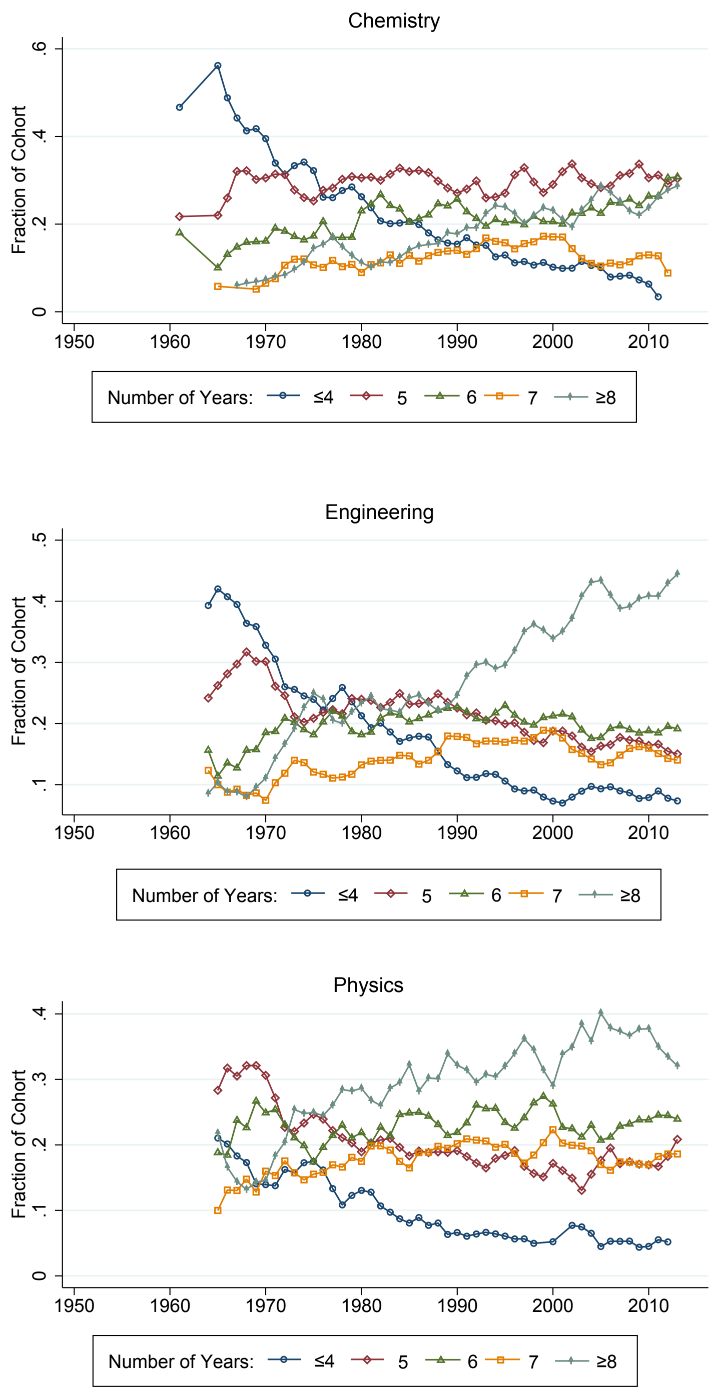


Figure B.3: Distribution of Years in Graduate School by Ph.D. Cohort for Additional Fields

Notes: These graphs give the three-year moving distribution of chemistry (top), engineering (middle), and physics (bottom) Ph.Ds.' years spent in graduate school, defined as the time between the Bachelor's and Ph.D. graduation year minus the number of years spent out of school during this time. Years are rounded down to the nearest integer. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown; some years are combined or suppressed due to low counts.

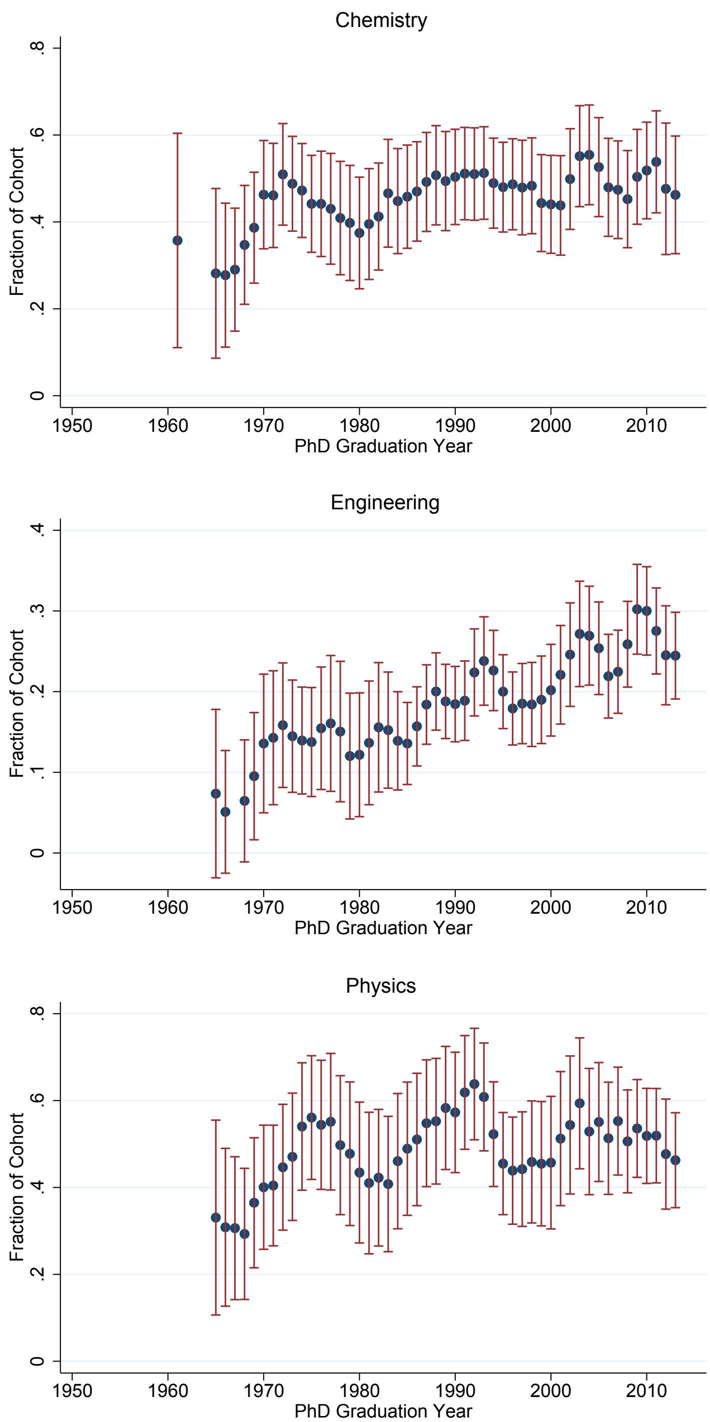


Figure B.4: Fraction Early Postdoctoral Takeup by Ph.D. Cohort for Additional Fields

Notes: These graphs give the three-year moving 95% confidence intervals for the fraction of each chemistry (top), engineering (middle), and physics (bottom) Ph.D. cohort that take on postdoctoral positions within two years of graduation. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown.

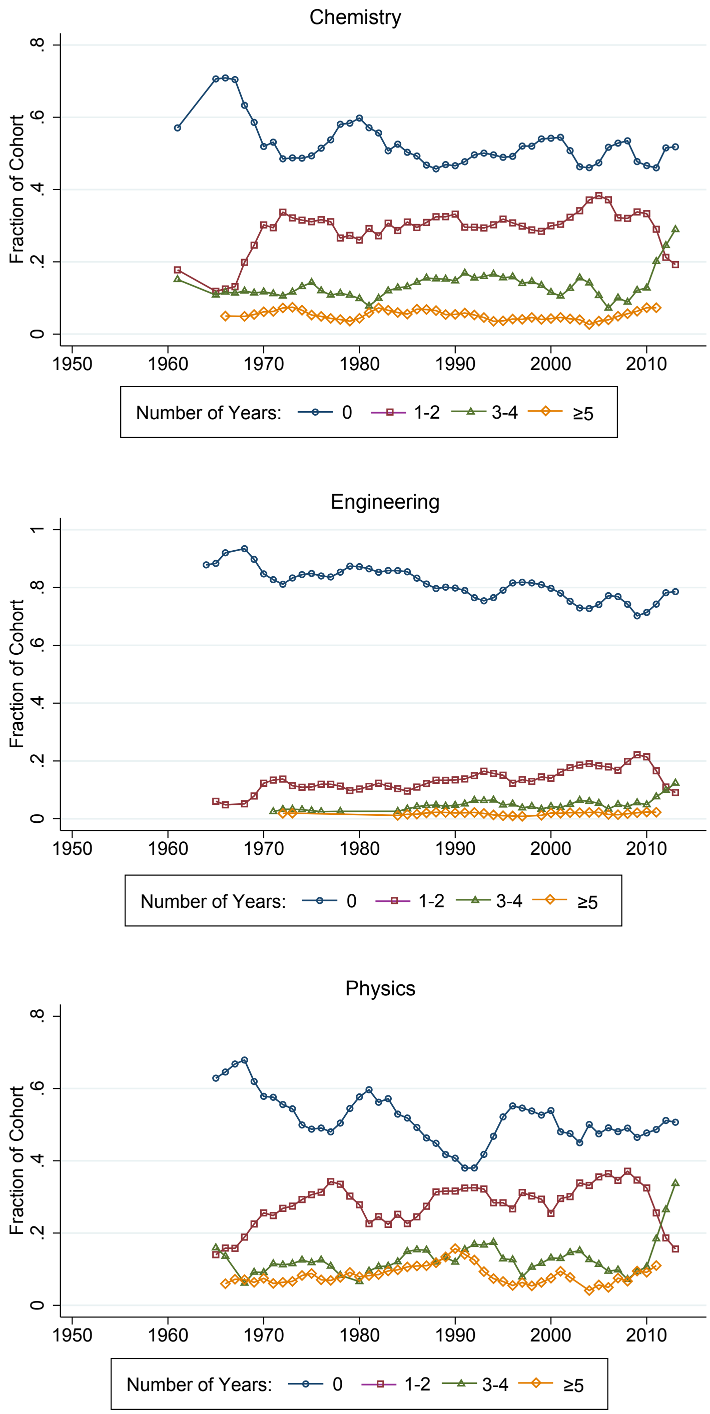


Figure B.5: Distribution of Postdoctoral Years by Ph.D. Cohort for Additional Fields

Notes: These graphs give the three-year moving distribution of chemistry (top), engineering (middle), and physics (bottom) Ph.Ds.' years observed in postdoctoral positions for each Ph.D. cohort. Half-years spent in postdoctoral positions are rounded down. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown; some years are combined or suppressed due to low counts.

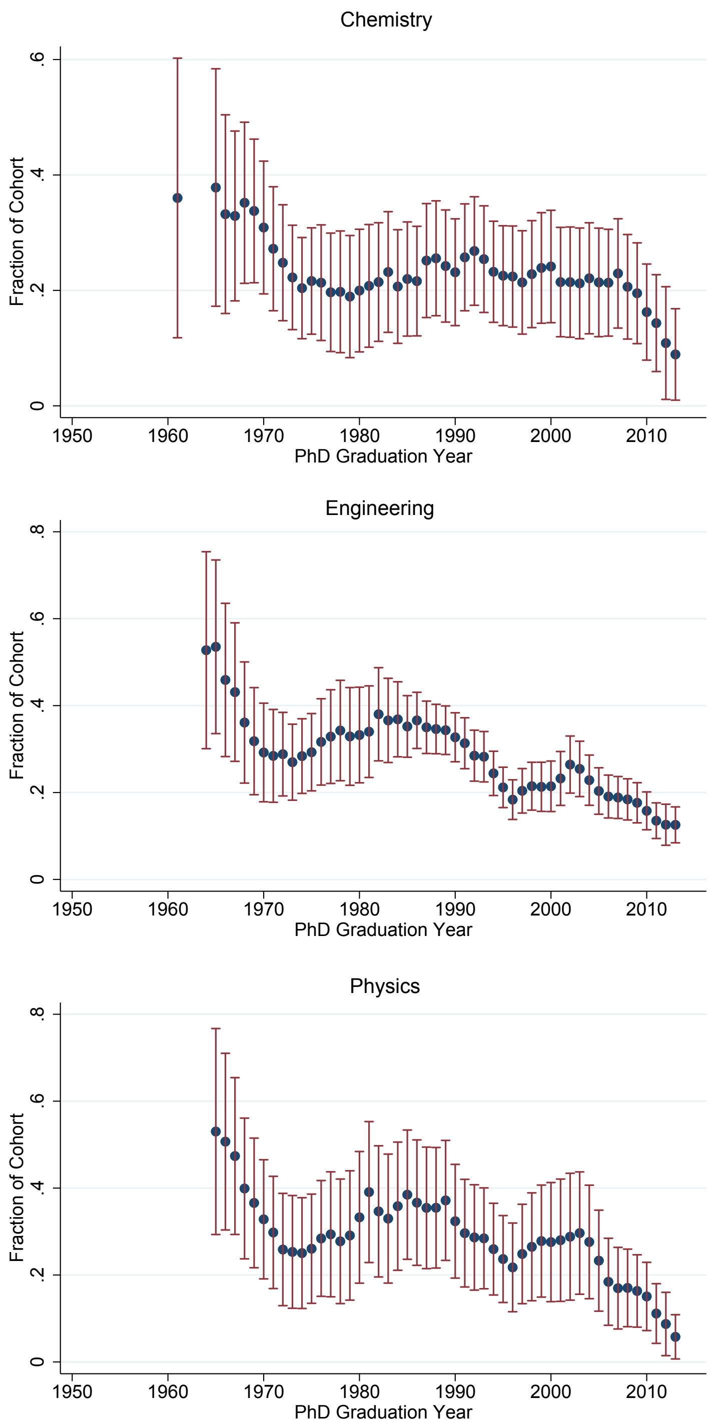


Figure B.6: Fraction Ever Observed in an Academic Tenure-Track Position by Ph.D. Cohort for Additional Fields

Notes: These graphs give the three-year moving 95% confidence intervals for the fraction of each chemistry (top), engineering (middle), and physics (bottom) Ph.D. cohort that is ever observed in an academic tenure-track position. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown.

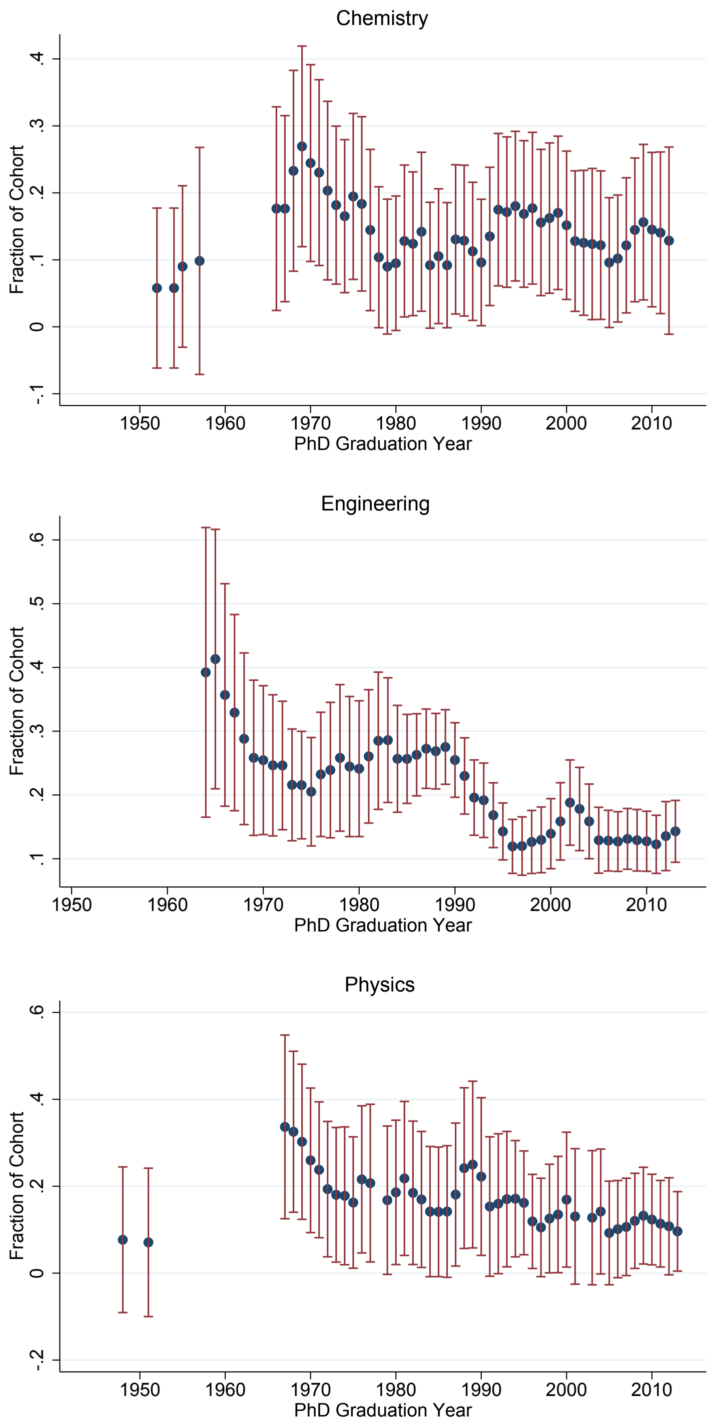
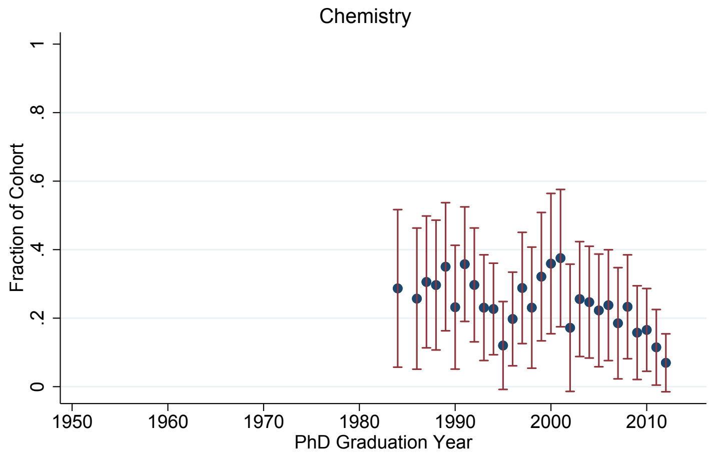
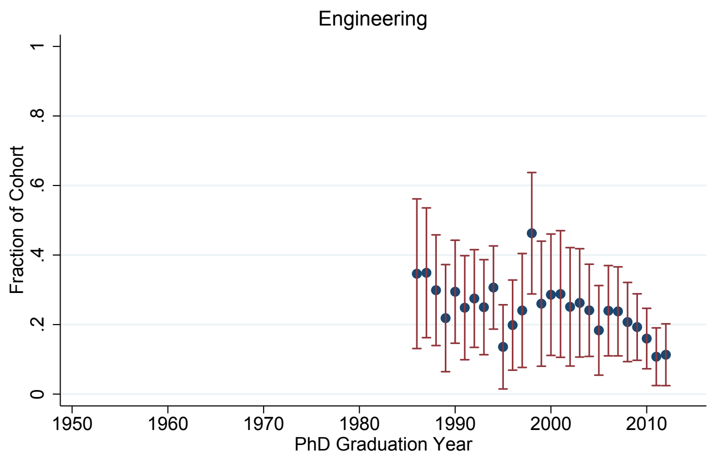


Figure B.7: Fraction Observed in an Academic Tenure-Track Position with No Postdoctoral Experience by Ph.D. Cohort for Additional Fields

Notes: These graphs give the three-year moving 95% confidence intervals for the fraction of each chemistry (top), engineering (middle), and physics (bottom) Ph.D. cohort observed in an academic tenure-track position within two years of their Ph.D. graduation without any postdoctoral experience. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown.





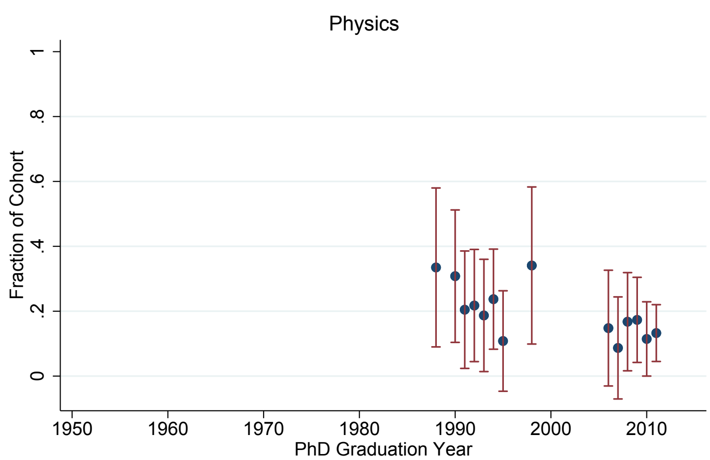
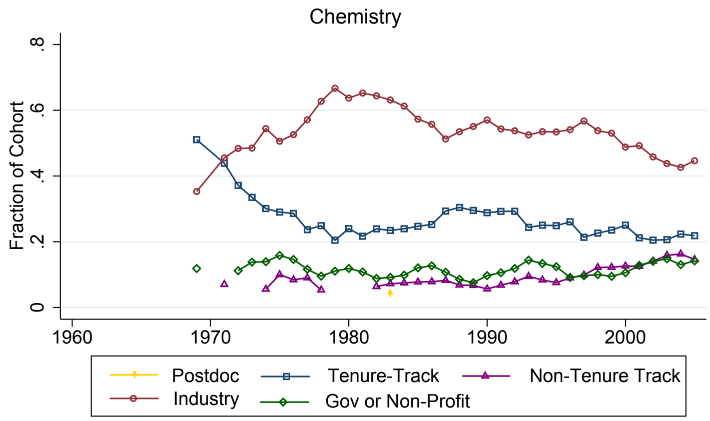
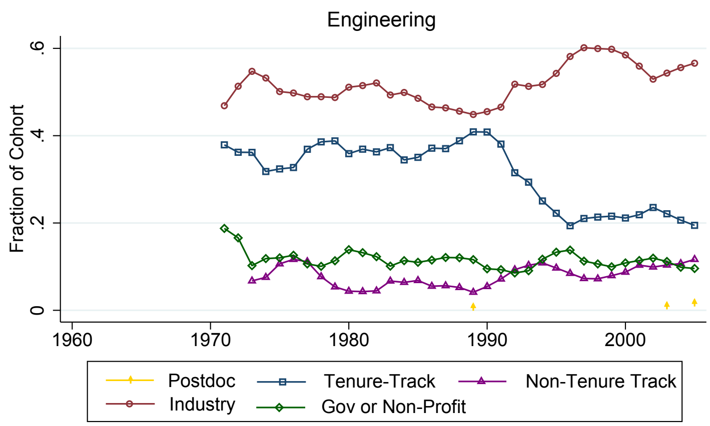


Figure B.8: Fraction Transition from Postdoctoral Position to an Academic Tenure-Track Position by Ph.D. Cohort for Additional Fields

Notes: These graphs give the three-year moving 95% confidence intervals for the fraction of postdoctoral researchers from each chemistry (top), engineering (middle), and physics (bottom) Ph.D. cohort who transition to an academic tenure-track position within two years of their last postdoctoral position. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown.





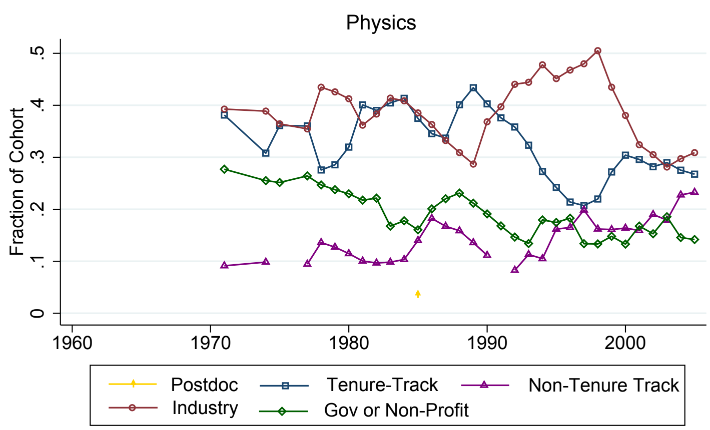


Figure B.9: Job Distributions Ten Years Post-Ph.D. Graduation for Additional Fields

Notes: This graph gives the three-year moving fraction of each chemistry (top), engineering (middle), and physics (bottom) Ph.D. cohort working ten years post-Ph.D. graduation in each job type. Individuals who are not working or do not have data ten years post-Ph.D. are not included. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown.

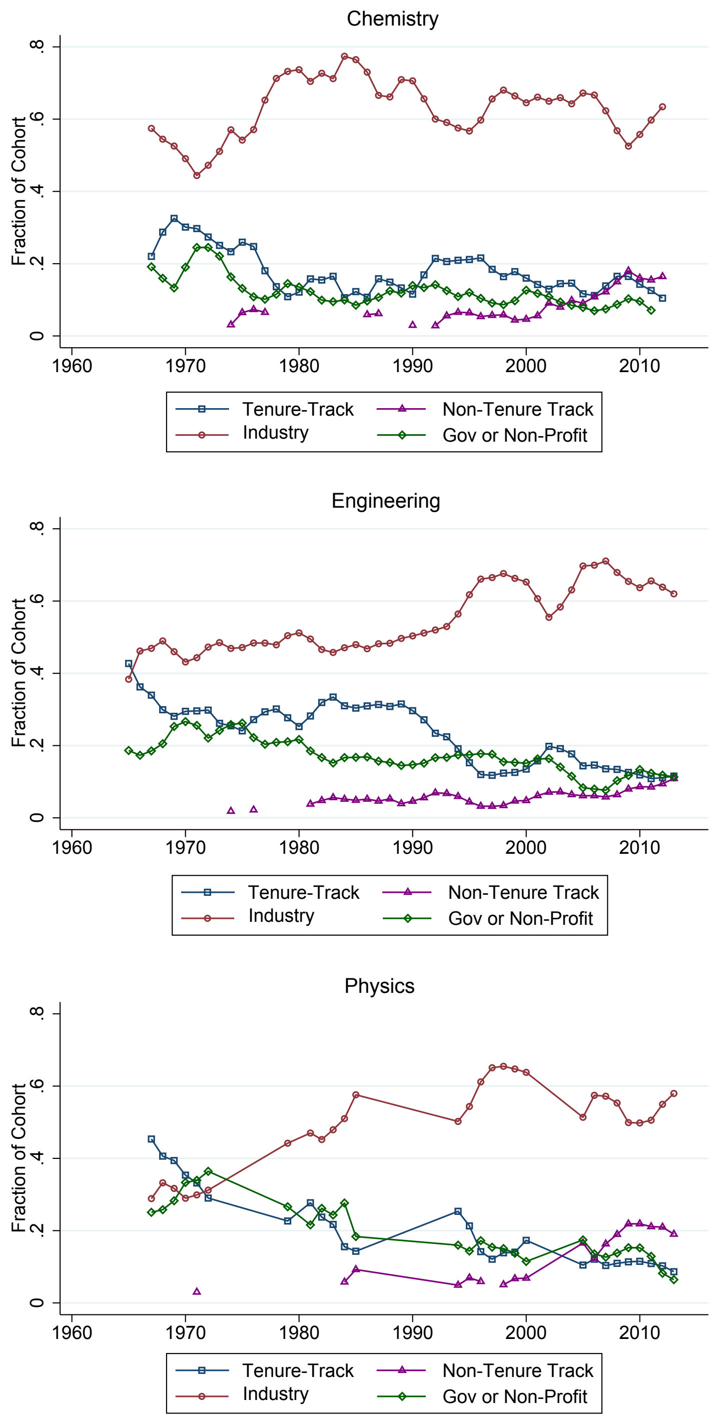


Figure B.10: Distribution of Non-Postdoc Job Transitions After Ph.D. Graduation by Ph.D. Cohort for Additional Fields

Notes: These graphs give the three-year moving distribution of each chemistry (top), engineering (middle), and physics (bottom) Ph.D. cohort who do not have postdoctoral experience that transition into each non-postdoc job type within two years of their graduation. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown; some job types are combined or suppressed due to low counts.

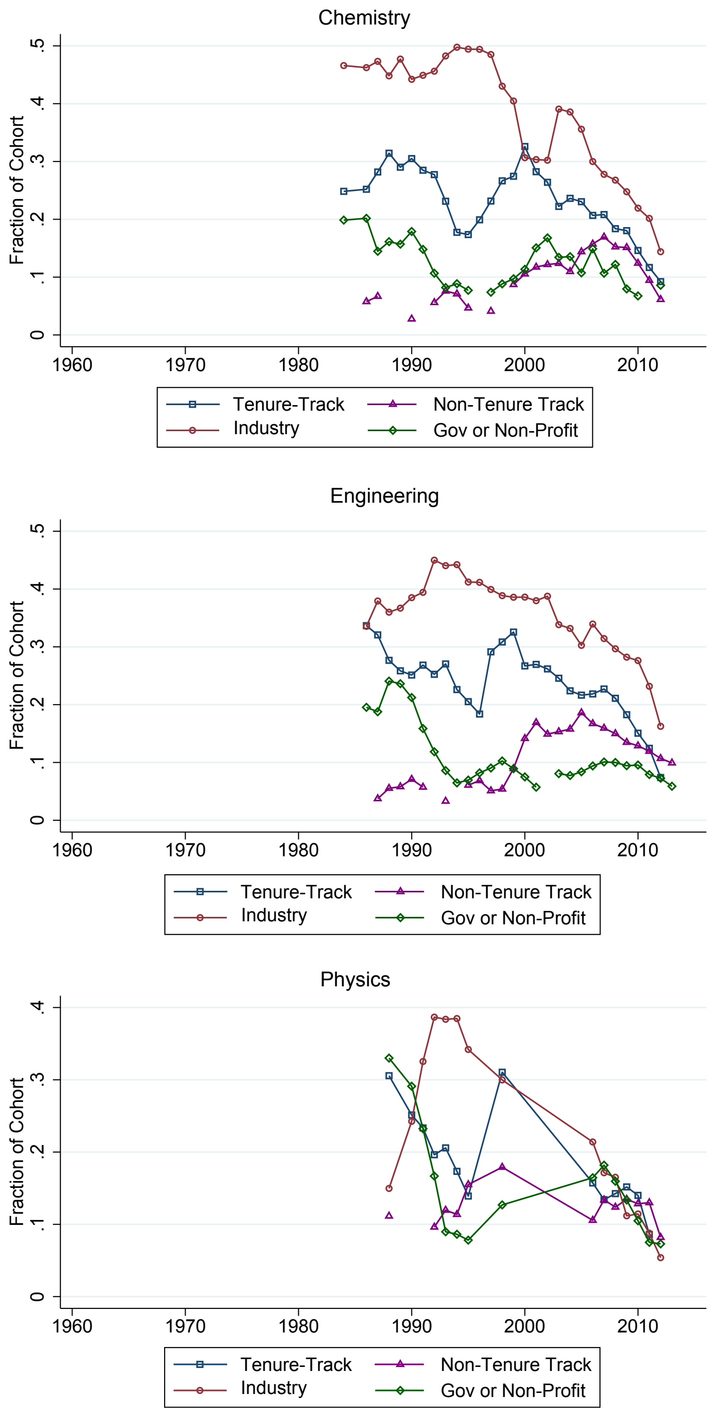


Figure B.11: Distribution of Job Transitions After Last Postdoctoral Appointment by Ph.D. Cohort for Additional Fields

Notes: These graphs give the three-year moving distribution of each chemistry (top), engineering (middle), and physics (bottom) Ph.D. cohort who have postdoctoral experience that transition into each non-postdoctoral job types within two years of their last postdoctoral position. For disclosure purposes, only cohorts with at least fifty individuals and cells with at least five individuals are shown; some job types are combined or suppressed due to low counts.

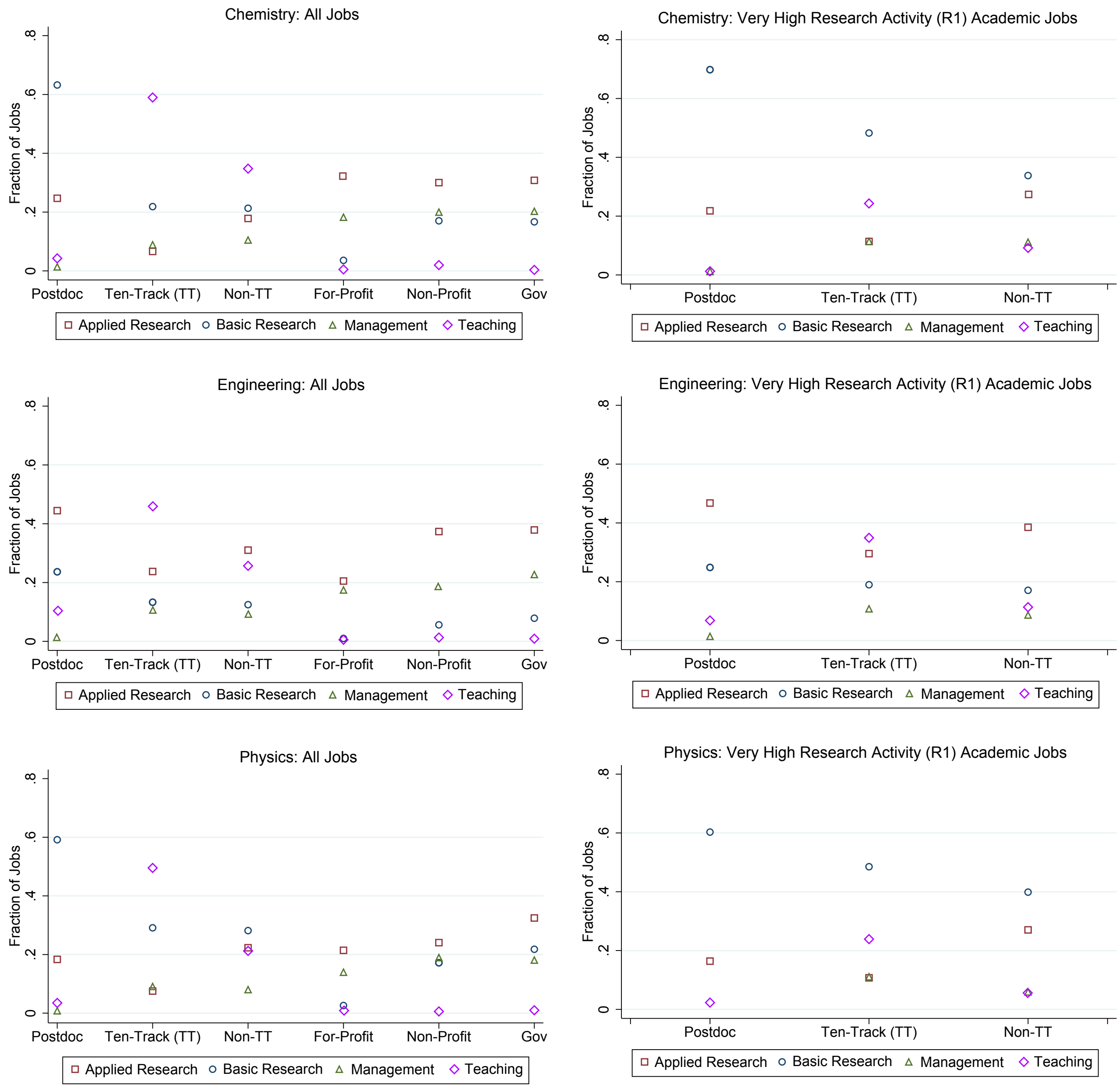


Figure B.12: Most Common Work Activity by Job Type for Additional Fields

Notes: These graphs give the fraction of chemistry (top row), engineering (middle row), and physics (bottom row) Ph.Ds. holding each job type during the survey period (1993-2015) that state they spend the most work hours on applied research, basic research, management, or teaching. Right column limits to academic sector jobs (postdoctoral, tenure-track, non-tenure track) at R1 Carnegie-Classified R1 "very high research activity" universities.

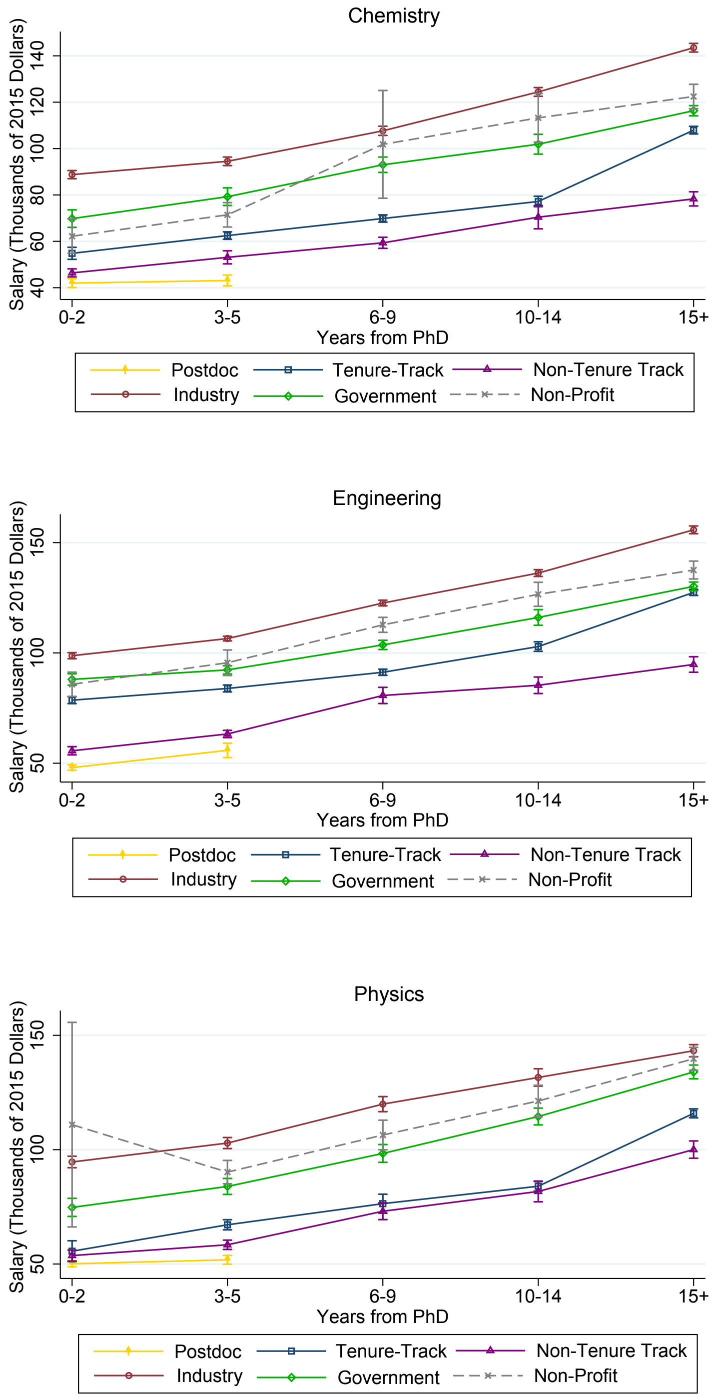


Figure B.13: Average Salary by Job Type and Career Stage for Additional Fields

Notes: This graph gives 95% confidence intervals for the inflation-adjusted salary during the survey period (1993-2015) of chemistry (top), engineering (middle), and physics (bottom) Ph.Ds. in six job types - postdoctoral researcher, academic tenure-track, academic non-tenure track, for-profit industry, non-profit, and government - grouped by years since Ph.D. graduation.

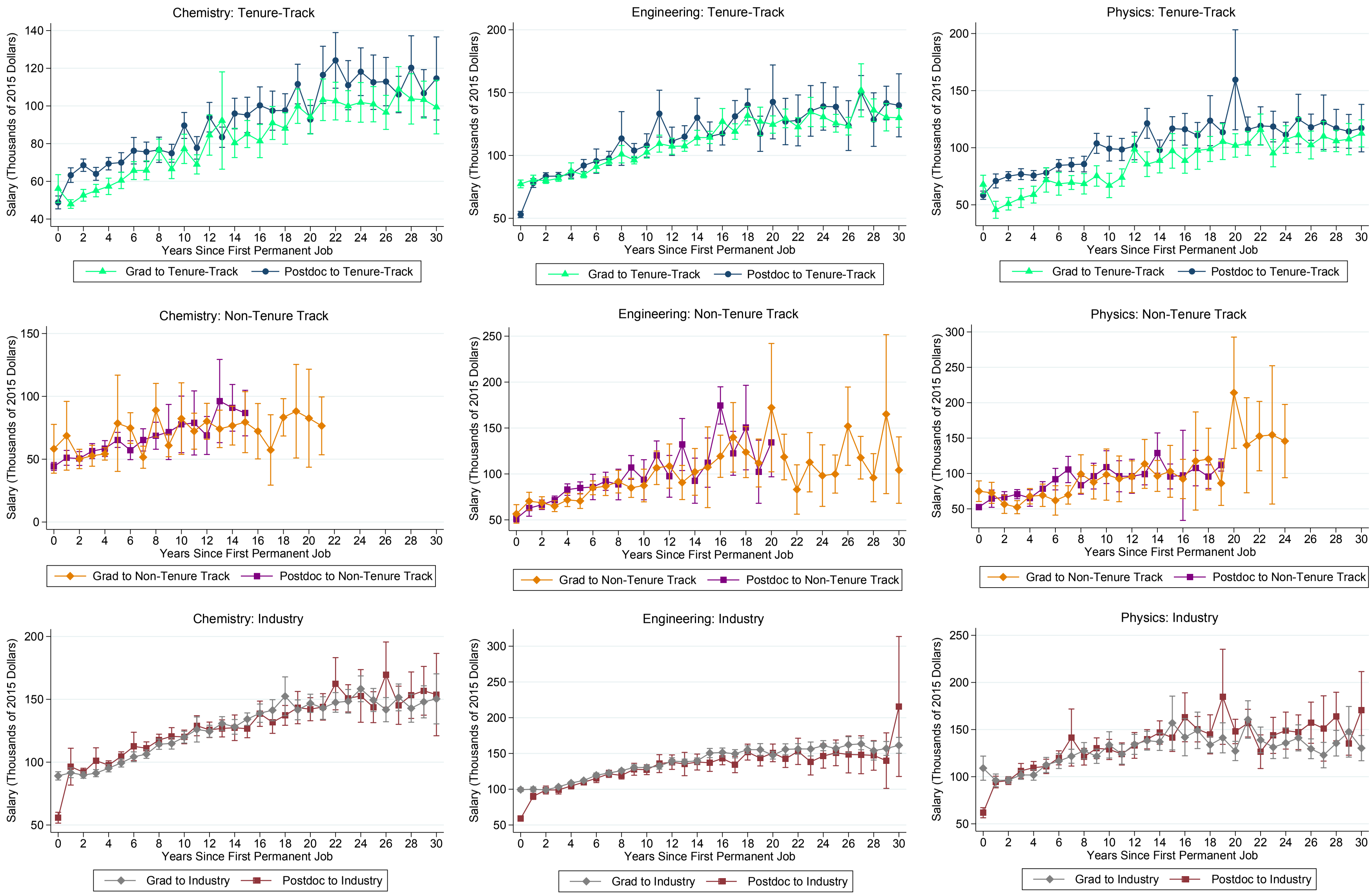


Figure B.14: Average Salary in Each Year Since First Permanent Job by Postdoctoral Path

Notes: These graphs give the average salary in tenure-track (top row), non-tenure track (middle row), and industry (bottom row) jobs for the first thirty years after starting a non-postdoctoral job type among chemistry (left column), engineering (middle column), and physics (right column) Ph.Ds., grouped by whether the individual pursued any postdoctoral experience. The first permanent job year is the Ph.D. graduation year for individuals transitioning directly from graduate school and is the last postdoctoral appointment year for individuals transitioning from a postdoctoral position.

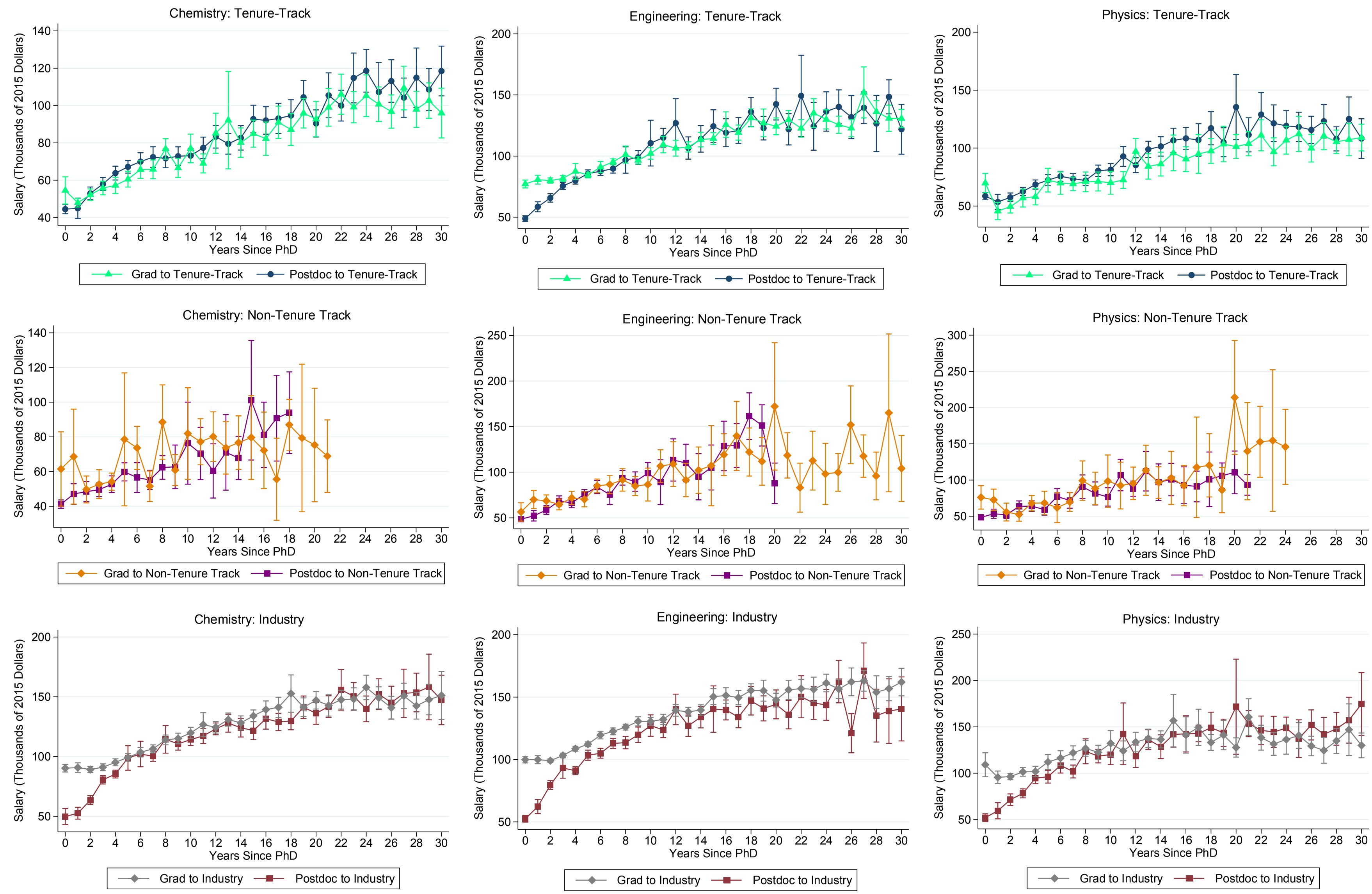


Figure B.15: Average Salary in Each Year Since Ph.D. Graduation by Postdoctoral Path

Notes: These graphs give the average salary in tenure-track (top row), non-tenure track (middle row), and industry (bottom row) jobs for the first thirty years after Ph.D. graduation amonng chemistry (left column), engineering (middle column), and physics (right column) Ph.Ds., grouped by whether the individual pursued any postdoctoral experience.

C Child Birth Years Algorithm

This appendix details the methodology used to identify a SDR individual's total number of children and estimate their children's birth years. It performs the methodology on the example Ph.D. whose child age bins across survey waves are given in Appendix Table C.1. Note that this data has been constructed for example purposes and does not represent an actual individual in the SDR data.

Table C.1: Example Number of Child Age Bins for an Individual Ph.D. Across Survey Waves

Survey	Under 2 (1)	Ages 2-5 (2)	Under 6 (3)	Ages 6-11 (4)	Ages 12-17 (5)	Ages 18+ (6)	Ages 12-18 (7)	Ages 19+ (8)
1993			0	2	0	0		
1995	0	0		1	1	0		
1997	0	0		0	2	0		
1999	0	0		0	2	0		
2006	0	1		0			0	1
2008	1	1		0			0	0
2010	0	1		1			0	0

Notes: This table gives an example of the raw survey responses giving an individual Ph.D.'s number of children in each age bin. Missing values indicate that this age bin was not included in that survey wave. Note that this individual Ph.D. did not respond to the 2003 survey wave.

To track a Ph.D.'s number of children over time, I construct a "ticker" system that counts the number of children that pass each age bin (see Appendix Table C.2). The example individual in 1995 has one child between ages 6-11 and one child between ages 12-17; thus, the ticker reads two for the "under 2", "2-5", and "6-11" age bins that both children pass and one for the "12-17" age bin that the oldest child passes. Across survey waves, these tickers only decrease if a child leaves the household; the largest decrease gives the number of children who leave in that year. 2006 and 2008 see tickers decrease by no more than one; this indicates one child has left in each of those years. Once I account for children who have left the household, new children are identified by the increase in the smallest age indicator. Adding on the running total of children who have left the household to the number in the "under 2" age bin, this smallest ticker increases from two to three in 2006 and three to four in 2008; this indicates that a new child is introduced to the family in those years. The total number of children is thus given by the max across survey waves of children observed in the survey plus the running total of children who have left the household. Thus, the example individual has four children, which is the max of the sum of the "under 2" age bin and the number of children who have left the household.

Table C.2: Example Ticker System: Number of a Ph.D.'s Children Passing Each Age Bin

Survey	Under 2 (1)	Ages 2-5 (2)	Under 6 (3)	Ages 6-11 (4)	Ages 12-17 (5)	Ages 18+ (6)	Ages 12-18 (7)	Ages 19+ (8)	Children Left (9)	New Children (10)	Total Children (11)
1993			2	2	0	0			0	0	2
1995	2	2		2	1	0			0	0	2
1997	2	2		2	2	0			0	0	2
1999	2	2		2	2	0			0	0	2
2006	2	2		1			1	1	1	1	3
2008	2	1		0			0	0	2	1	4
2010	2	2		1			0	0	2	0	4

Notes: Columns 1-8 of this table give the example individual Ph.D.'s "tickers" for the number of their children that have passed by each age bin in each survey wave. Missing values indicate that this age bin was not included in that survey wave. Column 9 gives a running count of the number of children who have left the household, based off decreases in the "tickers" from columns 1-8. Column 10 gives the number of new children in that survey year, given by increases in the "tickers" from columns 1-8 after accounting for the number of children who have left in column 9. Column 11 gives the total number of chilldren identified in that survey year, given by the sum of the smallest "ticker" ("under 2" in column 1) and the number of children who have left the household (in column 9).

Once I've identified the total number of children, I can break down the grouped age bins provided in the survey into individual child age indicators (see Appendix Table C.3). From my assumption on the chronological ordering of children, I attribute the leftmost age (or new child birth) indicator to the youngest child and the rightmost age (or child leave) indicator to the oldest child. For example, the latest new child birth is given in 2008 and thus attributed to the fourth child; in that same year, the oldest child is in the running total of children who have left the household. Working two children at a time from the outer to inner indicators, I thus identify the Nth oldest and Nth youngest child's age indicators with each cycle through the algorithm. This process can be repeated indefinitely for families of any size, but the vast majority (99 percent) of the sample has fewer than five children. I keep the process to Ph.Ds. with fewer than five children to reduce computational time.

Table C.3: Example Tickers Broken-Down Into Individual Child Indicators

Survey	Under 2 (1)	Ages 2-5 (2)	Under 6 (3)	Ages 6-11 (4)	Ages 12-17 (5)	Ages 18+ (6)	Ages 12-18 (7)	Ages 19+ (8)	Children Left (9)
1993			0	B A	0	0			0
1995	0	0		B	A	0			0
1997	0	0		0	B A	0			0
1999	0	0		0	B A	0			0
2006	0	C		0			0	B	A
2008	D	C		0			0	0	B A
2010	0	D		C			0	0	B A

Notes: This table breaks down the "ticker" age bins into each child's individual age indicators. A represents the first child, B represents the second child, C represents the third child, and D represents the fourth child. This table was constructed by first identifying A and D's age ranges in each survey wave as the last and first indicators respectively; these were then removed from the "tickers," then B and C's age ranges in each survey waves were identified by the remaining last and first indicators respectively.

Once I have separated the grouped age bins into each individual child's age indicators, I calculate the range of possible birth years for each child from the extreme values of the age ranges (see Appendix Table C.4). Because a child's actual birth year must fall within all ranges given by their age indicators, I reduce the estimated birth year range to {max(range start years), min(range end years)}. This narrows the first child's birth years to 1982-1983; the second child's birth years to 1984-1985; the third child's birth years to 2003-2004; and the fourth child's birth years to 2006-2008. If the end of one child's birth range is after the start of their nearest younger sibling, I further reduce the older sibling's end range with their younger sibling's start range. This does not occur in the example; however, if the first child's birth year had instead narrowed down to 1982-1985, it could have been reduced to 1982-1984 based on the start year of the second child.

Table C.4: Example Estimation of Child Birth Years

	1st Child				2nd Child		
Survey	Age Bin (1)	Start (2)	End (3)	Survey	Age Bin (4)	Start (5)	End (6)
1993	6-11	1981	1986	1993	6-11	1981	1986
1995	12-17	1978	**1983**	1995	6-11	**1984**	1989
1997	12-17	1980	1985	1997	12-17	1980	**1985**
1999	12-17	**1982**	1987	1999	12-17	1982	1987
2006				2006	19+		1987
2008				2008			
2010				2010			

	3rd Child				4th Child		
Survey	Age Bin (7)	Start (8)	End (9)	Survey	Age Bin (10)	Start (11)	End (12)
1993				1993			
1995				1995			
1997				1997			
1999				1999			
2006	2-5	2001	**2004**	2006			
2008	2-5	**2003**	2006	2008	<2	**2006**	**2008**
2010	6-11	1999	**2004**	2010	2-5	2005	**2008**

Notes: This table gives the birth year ranges for each of the example individual Ph.D.'s four children, based on which age bin indicator they have in each survey wave. The estimated birth year range is bolded and given by the latest possible start year (columns 2, 5, 8, and 11) and the earliest possible end year (columns 3, 6, 9, and 12) for each child.

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