Careers Versus Children:
How Childcare Affects the Academic Tenure-Track Gender Gap

Stephanie D. Cheng*
Harvard University
(Job Market Paper)

November 11, 2020
(Click here for most recent version)

Abstract

Although women compose the majority of biological science Ph.D. recipients, those who have children are 7 percentage points less likely than their male peers to ever obtain a tenure-track position - leading to a mere 30 percent female among tenure-track faculty. Using the largest nationally representative survey of U.S. Ph.D. recipients, this paper examines how a biological science Ph.D.'s first child's birth affects employment status and job characteristics by gender. I find no gender gap in tenure-track rates among individuals who never have children and among individuals before they have children. 9 percent of mothers temporarily leave the labor force after their first child is born; those who remain reduce working hours by 12 percent, compared to fathers who reduce by 6 percent. Mothers return to the labor force when their children reach school-age but shift away from tenure-track positions, leading to a 10 percentage point gender gap among tenure-track faculty with six-year-old children. However, mothers do not leave research occupations with fewer work hours, such as industry and non-tenure track positions. I conclude that short-term work reductions to focus on childcare combined with a competitive profession requiring long hours leads to long-term reductions in promotions, increasing the gender gap at the top levels of academia.

***Contact:** stephaniecheng@g.harvard.edu, Harvard University Department of Economics
Acknowledgements: I am grateful to Claudia Goldin, Lawrence Katz, and Amanda Pallais for their comments, suggestions, and support. I also want to thank Richard Freeman, Donna Ginther, Shulamit Kahn, Megan Macgarvie, Robert Siliciano, Wei Yang Tham, Bruce Weinberg, and seminar participants at Harvard University, NBER-IFS International Network on the Value of Medical Research, and NBER Productivity Working Group for their feedback. Thanks also to Patrick Lin, Irina Pushel, Hosea Siu, Matthew Turner, Linda Xu, and the National Postdoctoral Association for their insight on STEM Ph.D. career paths. This project was generously supported by the National Institute on Aging (NIA) through grant R24AG058049 to the National Bureau of Economic Research (NBER) with data provided by the National Science Foundation (NSF). All errors are my own. The content of this paper is solely the responsibility of the author and does not necessarily represent the official views of the NIA, NBER, or NSF.

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 have composed the majority of biological science Bachelor's, Master's, and Ph.D. recipients since 2007 (*Science and Engineering Indicators* 2018). However, even with impressive gains in gender parity at the trainee level, women remain underrepresented at the higher rungs of the academic ladder: 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 their 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 precise timing of the first child's birth.[1] 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 et al. 2018, Bentley and Adamson 2003, Jolly et al. 2014, Parker and Wang 2013).[2] 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 et al. 2010).[3] Family-related reasons are by far the most common factor that mothers state for their changes in work situations. Although mothers return 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-intensity 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 trainee level, as scientist-mothers leave for jobs with fewer work hours in industry and non-tenure track, a persistent gender

[1]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 et al. 2020, Martinez et al. 2007, Mason et al. 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.

[2]The closing of childcare centers during the recent COVID-19 pandemic has exasperated this tension: 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% of the gender gap in the biological sciences' academic promotion rates.

[3]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.

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.[4] Using a novel algorithm, I exploit the survey's longitudinal structure to triangulate possible child birth years 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, tenure-track academic, non-tenure track academic, and for-profit industry) or is out of the labor force.[5] 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.[6] These gender gaps persist even as their children grow older and mothers return to the labor force.

The child penalty observed on the tenure track does not appear in other job types, even within the

[4]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.

[5]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. My previous work, Cheng (2020), 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.

[6]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).

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 non-tenure track academic 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. Non-tenure track positions also have a similar focus on research activities, with 39% of employees spending the most time on basic research compared to 36% of tenure-track employees.[7] There is also no evidence of a lower quality research environment off the tenure track: although female academics are concentrated in non-tenure track positions, they are as likely to be at a Carnegie-classified "high research activity" institution as male academics before and after having children.[8] 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-intensity 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.[9]

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 precise timing of a first child's birth to parental career trajectories. Through a novel identification strategy, I show how individual child birth years can be extracted from repeated observations of grouped family data. I demonstrate that women's reduced 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

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

[8] The Carnegie Classification system groups academic institutions by the number of doctoral degrees conferred and total research expenditures each year. A "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.

[9] 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 better 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).

work time pushes 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 stopper 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 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 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 the estimation techniques used to link children and careers together.[10] Section 4 presents the main results and evidence for long work hours as the driving mechanism. Section 5 discusses potential avenues for future research and concludes.

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.[11] 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.,[12] or are otherwise unable to respond.[13]

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

[10] Further detail on these methodologies are given in Appendices A and B.

[11] Appendix C gives the full distribution of fields. This paper focuses on Ph.D. fields categorized as "biological/biomedical sciences", which are also listed in the appendix.

[12] 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.

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

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 relatively high at 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 13). Thus, it is possible for individuals to miss multiple waves but respond later. For the 1993-2015 SDR waves, Table 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 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.

3 Methodology

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 each child's possible birth years.[14] 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.

Once a Ph.D.'s total number of children is identified, I construct an algorithm to estimate a range of possible birth years for each child. This is done by breaking down the total number of children in select

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

age bins into each individual child's age indicators.[15] 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. However, without further information from the survey, I would be unable to identify the correct child.

I then determine the possible birth years that fall within each child's set of age indicators across survey waves. Table 2 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. I make this restriction to 1990-1999 Ph.D. graduation years as it gives the largest sample of biological scientists that are observed for at least ten years. In the majority of cases, the algorithm reduces the first child's birth down to one or two possible years. A small percentage of individuals have an error in which the estimated range 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.[16] 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, the respondent may have only answered one survey wave in the time they have children in the household. Without further survey information, I cannot reduce the range below those given by the age indicators.

To determine the concurrent parental job in each year, I construct career paths across six job types and two non-employed statuses.[17] 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, tenure-track academic, non-tenure track academic, 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.[18] 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.

[15]To reduce computational time, I have limited the sample to Ph.Ds. with a maximum of five children (99 percent of the sample).

[16]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.

[17]This methodology was developed in previous work, Cheng (2020), as an expansion of Ginther and Kahn (2017)'s estimation of postdoctoral incidence. For more detail on the career path construction and a hypothetical example using this methodology, see Appendix B.1 .

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

3.2 Linking Children to Careers

Before describing the main analyses, I present summary statistics for the sample by gender and parental status. Table 3 gives demographics for men and women who are never observed with children and for men and women who are ever observed with children. Individual characteristics such as race, citizenship, and education are relatively balanced across gender and parental status, suggesting that the variation I exploit is not confounded by these demographic differences. There are, however, clear gender differences in employment type and job characteristics. Table 4 gives summary statistics on experience in each job type and employment status. The gender gap in tenure-track positions among parents is more than twice the gender gap among non-parents, and the gender gap in labor force participation is nearly three times as large among parents as compared to non-parents. Table 5 gives summary statistics on job characteristics. The salary gender gap is more than three times larger among 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 6 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.[19]

For the main analyses, I take the median year (rounding down) of each first child's birth year range to give the birth timing.[20] To control for 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 7 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 are putting off 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 the first five years post-Ph.D. to have children than fathers. Having their first child at 34 years old, the average scientist-mother is also quickly

[19]Note that respondents can select multiple reasons for their changing work situations. It is possible that it is 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.

[20]By using the median year, I minimize measurement bias as the actual children's birth years would on average be evenly distributed across the survey age bins; thus, the median would overestimate the birth years for half of the age bin and underestimate the birth years for half of the age bin. As a robustness check, I have re-run analysis using the earliest year of the birth range; this does not significantly impact results.

approaching the "advanced maternal age" of 35 (Lean et al. 2017).

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 in each employment type for 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.[21] 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, it 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.[22] 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 can widely differ by sector, I include indicators for the four job types in these regressions.[23] These additional job type indicators control for selection into different occupations, which may confound the child effect.

[21] Any group characteristic that is linear with time, such as age, should be accounted for in the pre-trends.

[22] 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.

[23] For example, previous work 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 (Cheng 2020).

4 Results

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 1 gives no gender gap in the percent holding tenure-track positions in the ten years before the first child's birth.[24] 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. As a comparison, among individuals who are never observed having children, Figure 2 shows no consistent gender gap in tenure-track rates through the first ten years post-Ph.D. graduation. Controlling for time since Ph.D., Figure 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., though 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: 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. (Cheng 2020). These results remain when controlling for individual characteristics in the Column 2 of Table 8. 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 et al. 2020).

A gender gap is not observed in other job types, as shown in Figure 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.[25] 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 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 8, 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 gender gap in other job types, this indicates that a

[24]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.

[25]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.

particular characteristic of the tenure track is contributing to its gender gap that is not present in industry or other academic jobs.

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 fraction out of the labor force shown in Figure 6 or average hours worked shown in Figure 7.[26] 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 8 or average hours worked shown in Figure 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, suggesting 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 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. As shown in Figure 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 8: 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.

Individuals who remain in the workforce reduce their work hours after their first child is born. As shown in Figure 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 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 in the first 5 years post-Ph.D. 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

[26] 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.

characteristics, as given in Column 1 of Table 9: both fathers and mothers reduce their working hours when they have children, but mothers reduce by approximately 3 times as much as fathers.

Tenure-track positions have the highest average weekly work hours of the permanent job types, as shown in Figure 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. However, 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 tenure-track to other permanent positions, non-tenure track and for-profit industry work 4 and 6 fewer hours per week respectively. Their average weekly hours are similar to women's reduced work hours after the first child's birth given in Figure 9, suggesting that these positions may better align with the schedules of working mothers. Figures 14 and 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.

Working hours is the most striking difference between tenure-track jobs and other permanent job types in explaining the gender gap. As shown in Figure 16, a larger percent 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, who appear to split time between research and teaching. Additionally, non-tenure track jobs are also in the academic sector and share a similar work environment as tenure-track jobs. 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 17 finds no gender gap in the fraction of individuals in Carnegie-Classified "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.

Mothers' selection into occupations with lower hours is at the cost of fewer promotions and salary raises. A raw comparison of salary in Figure 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 9. 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 9, women lose approximately 7% of their salary from having children; this salary gap grows by approximately 2% each year, even as their children grow older and mothers return to the labor force.

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 an individual child's birth year can be extracted from repeated observations of grouped family 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, tenure-track academic, non-tenure track academic, 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 precise 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. This "sagging middle" in labor force participation occurs at any point in a 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 gender gap does not appear among individuals holding postdoctoral, for-profit industry, or non-tenure track academic 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, with women 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. There is no evidence that non-tenure track positions are in lower quality research environments than tenure-track positions, as women are as likely as men to be in Carnegie-Classified "high research activity" institutions before and 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-intensity 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.[27] 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.[28] 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.

[27] 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).

[28] Antecol et al. (2018) find that gender-neutral tenure clock stopping policies actually reduces female tenure rates and substantially increases male tenure rates, as 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.

References

A current glance at women in the law. (2006). Retrieved from https://www.americanbar.org/content/dam/aba/administrative/women/CurrentGlanceStatistics2006.pdf

Antecol, H., Bedard, K., & Stearns, J. (2018). Equal but inequitable: Who benefits from gender-neutral tenure clock stopping policies? *American Economic Review*, *108*(9), 2420–2441.

Azmat, G., & Ferrer, R. (2015). Gender gaps in performance: Evidence from young lawyers. *IZA Discussion Paper*, (9417).

Bennett, B., Erel, I., Stern, L. H., & Wang, Z. (2020). (forced) feminist firms. *NBER Working Paper*, (27788).

Bentley, J. T., & Adamson, R. (2003). *Gender differences in the careers of academic scientists and engineers: A literature review*. Mathtech Inc. and National Science Foundation.

Bertrand, M., Goldin, C., & Katz, L. F. (2010). Dynamics of the gender gap for young professionals in the financial and corporate sectors. *American Economic Journal: Applied Economics*, *2*(3), 228–255.

Buffington, C., Cerf, B., Jones, C., & Weinberg, B. A. (2016). Stem training and early career outcomes of female and male graduate students: Evidence from umetrics data linked to the 2010 census. *American Economic Review*, *106*(5), 333–38.

Cech, E. A., & Blair-Loy, M. (2019). The changing career trajectories of new parents in stem. *Proceedings of the National Academy of Science*, *116*(10), 4182–4187.

Cheng, S. D. (2020). *What's another year? the lengthening training and career paths of scientists* (Doctoral dissertation, Harvard University). Dissertation Chapter.

Foley, D. J. (2015). *Survey of doctorate recipients, 2015 (technical notes)*. National Center for Science and Engineering Statistics. Retrieved from https://ncsesdata.nsf.gov/doctoratework/2015/sdr_2015_tech_notes.pdf

Ginther, D. K., & Kahn, S. (2009). *Ch. 5: Does science promote women? evidence from academia 1973-2001* (R. B. Freeman & D. Goroff, Eds.). University of Chicago Press.

Ginther, D. K., & Kahn, S. (2014). *Ch. 11: Academic women's careers in the social scientists* (A. Lanteri & J. Vromen, Eds.). Cambridge University Press.

Ginther, D. K., & Kahn, S. (2017). The impact of postdoctoral training on early careers in biomedicine. *Nature Biotechnology*, *35*(1), 90–94.

Goldin, C., & Katz, L. F. (2008). Transitions: Career and family life cycles of the educational elite. *American Economic Review: Papers and Proceedings*, *98*(2), 363–369.

Goldin, C., & Katz, L. F. (2011). The cost of workplace flexibility for high-powered professionals. *The ANNALS of the American Academy of Political and Social Science*, *638*(45), 45–67.

Goldin, C., & Katz, L. F. (2016). A most egalitarian profession: Pharmacy and the evolution of a family friendly occupation. *Journal of Labor Economics*, *34*(3), 705–745.

Goldin, C., Kerr, S. P., Olivetti, C., & Barth, E. (2017). The expanding gender earnings gap: Evidence from the lehd-2000 census. *American Economic Review: Papers and Proceedings*, *107*(5), 110–114.

Goldin, C., & Mitchell, J. (2017). The new life cycle of women's employment: Disappearing humps, sagging middles, expanding tops. *Journal of Economic Perspectives*, *31*(1), 161–182.

Jolly, S., Griffith, K. A., DeCastro, R., Stewart, A., Ubel, P., & Jagsi, R. (2014). Gender differences in time spent on parenting and domestic responsibilities by high-achieving young physician-researchers. *Annals of Internal Medicine*, *160*(5), 344–53.

Kim, S., & Moser, P. (2020). *Women in science: Lessons from the baby boom*. Presented at 2020 NBER Summer Institute.

King, M., & Frederickson, M. (2020). The pandemic penalty: The gendered effects of covid-19 on scientific productivity. *SocArXiV*. Retrieved from https://doi.org/10.31235/osf.io/8hp7m

Lean, S. C., Derricott, H., Jones, R. L., & Heazell, A. E. (2017). Advanced maternal age and adverse pregnancy outcomes: A systematic review and meta-analysis. *PLoS ONE*.

Lerchenmueller, M. J., & Sorenson, O. (2018). The gender gap in early career transitions in the life sciences. *Research Policy*, *47*(6), 1007–1017.

Mairesse, J., Pezzoni, M., & Visentin, F. (2020). Does gender matter for promotion in science? evidence from physicists in france. *NBER Working Paper*, (27789).

Martinez, E. D., Botos, J., Dohoney, K. M., Geiman, T. M., Kolla, S. S., Olivera, A., ... Cohen-Fix, O. (2007). Falling off the academic bandwagon. women are more likely to quit at the postdoc to principal investigator transition. *EMBO Reports*, *8*(11), 977–981.

Mas, A., & Pallais, A. (2017). Valuing alternative work arrangements. *American Economic Review*, *107*(12), 3722–59.

Mason, M. A., Wolfinger, N. H., & Goulden, M. (2013). *Do babies matter? gender and family in the ivory tower*. Rutgers University Press.

Myers, K. R., Tham, W. Y., Yin, Y., Cohodes, N., Thursby, J. G., Thursby, M. C., ... Wang, D. (2020). Unequal effects of the covid-19 pandemic on scientists. *Nature Human Behavior*, *4*, 880–883.

Nelson, D. J., & Brammer, C. N. (2010). *A national analysis of minorities in science and engineering faculties at research universities*. Diversity in Science Association.

Parker, K., & Wang, W. (2013). *Modern parenthood: Roles of moms and dads converge as they balance work and family*. Pew Research Center.

Science and Engineering Indicators. (2018). National Science Board, National Science Foundation. Retrieved from https://www.nsf.gov/statistics/indicators/

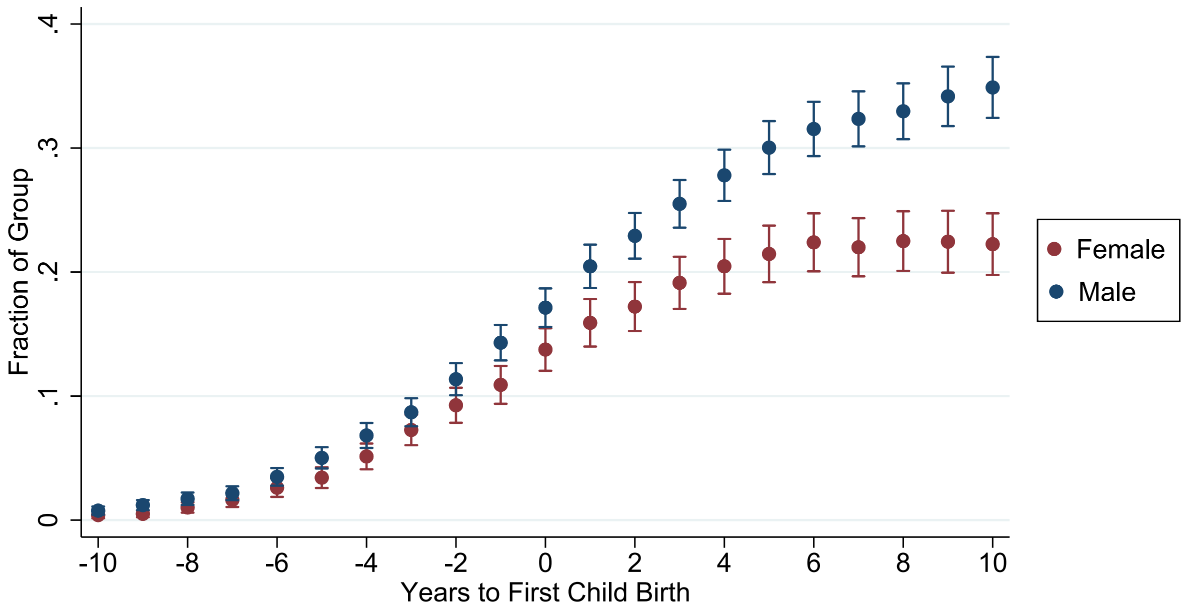
Tô, L. T. (2018). *The signaling role of parental leave* (Doctoral dissertation, Harvard University).

Wasserman, M. (2016). *Hours constraints, occupational choice, and gender: Evidence from medical residents* (Doctoral dissertation, Massachusetts Institute of Technology).

Zandberg, J. (2020). Family comes first: Reproductive health and the gender gap in entrepreneurship. *Journal of Financial Economics*.

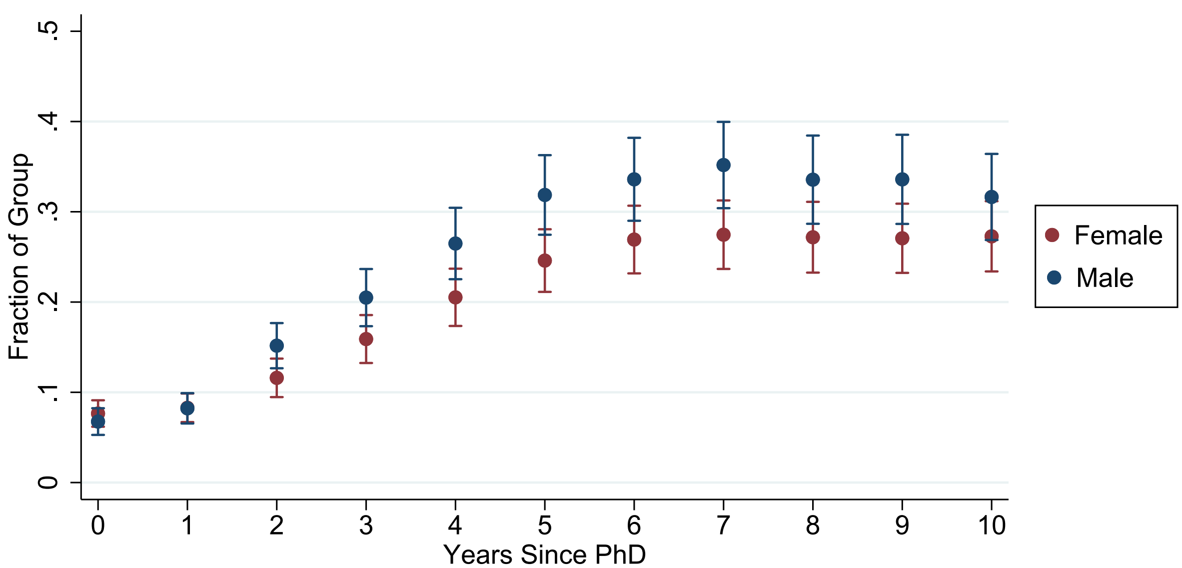
6 Figures

Figure 1: Fraction in Tenure-Track Positions Within Ten Years of First Child's Birth by Gender



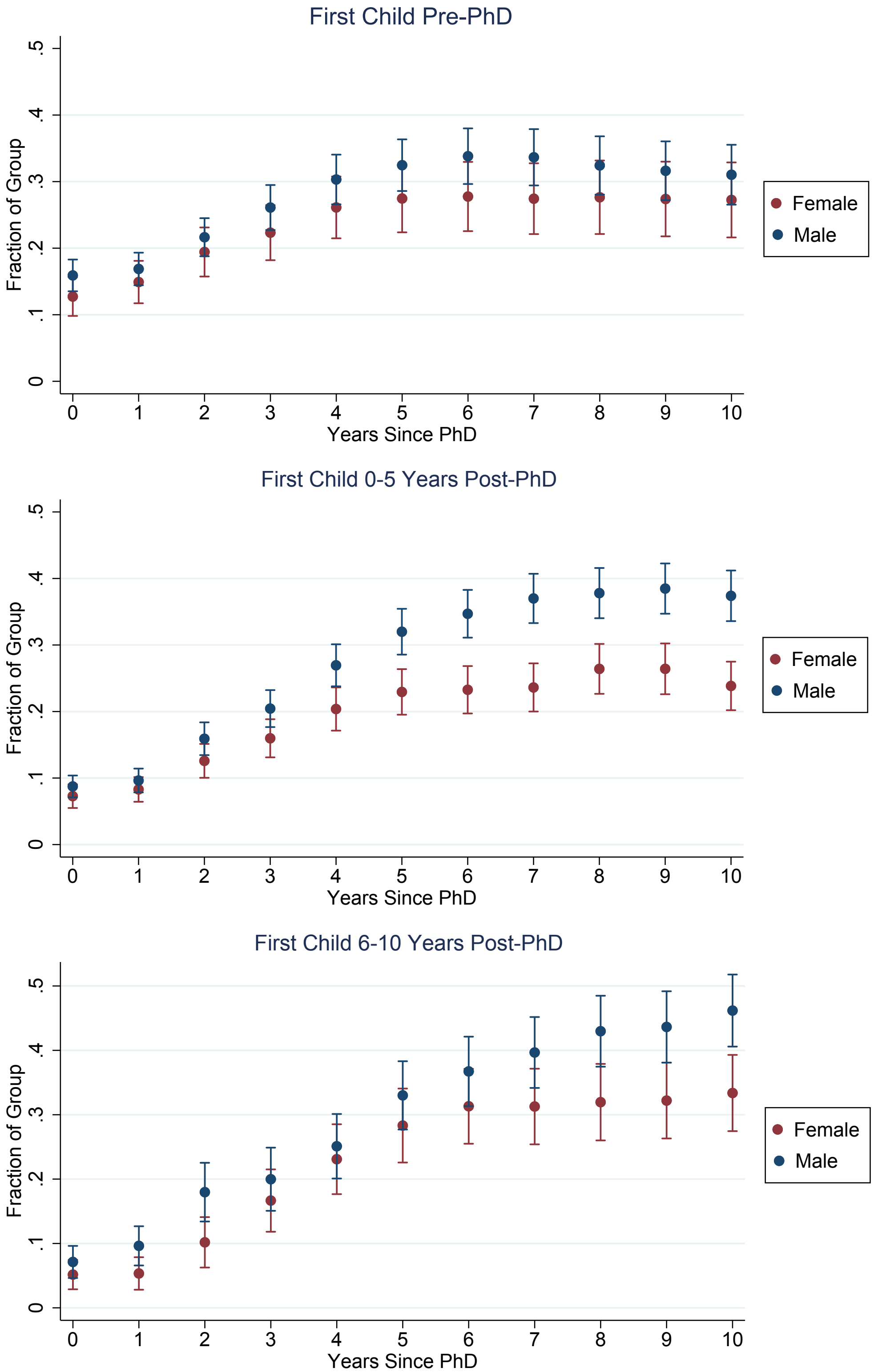
Notes: These graphs give the raw fraction of male and female biological science Ph.Ds. who become parents that are in tenure-track positions in the ten years before through the ten years after the birth of their first child.

Figure 2: Fraction in Tenure-Track Positions During First Ten Years Post-Ph.D. by Gender Among Ph.Ds. with No Children



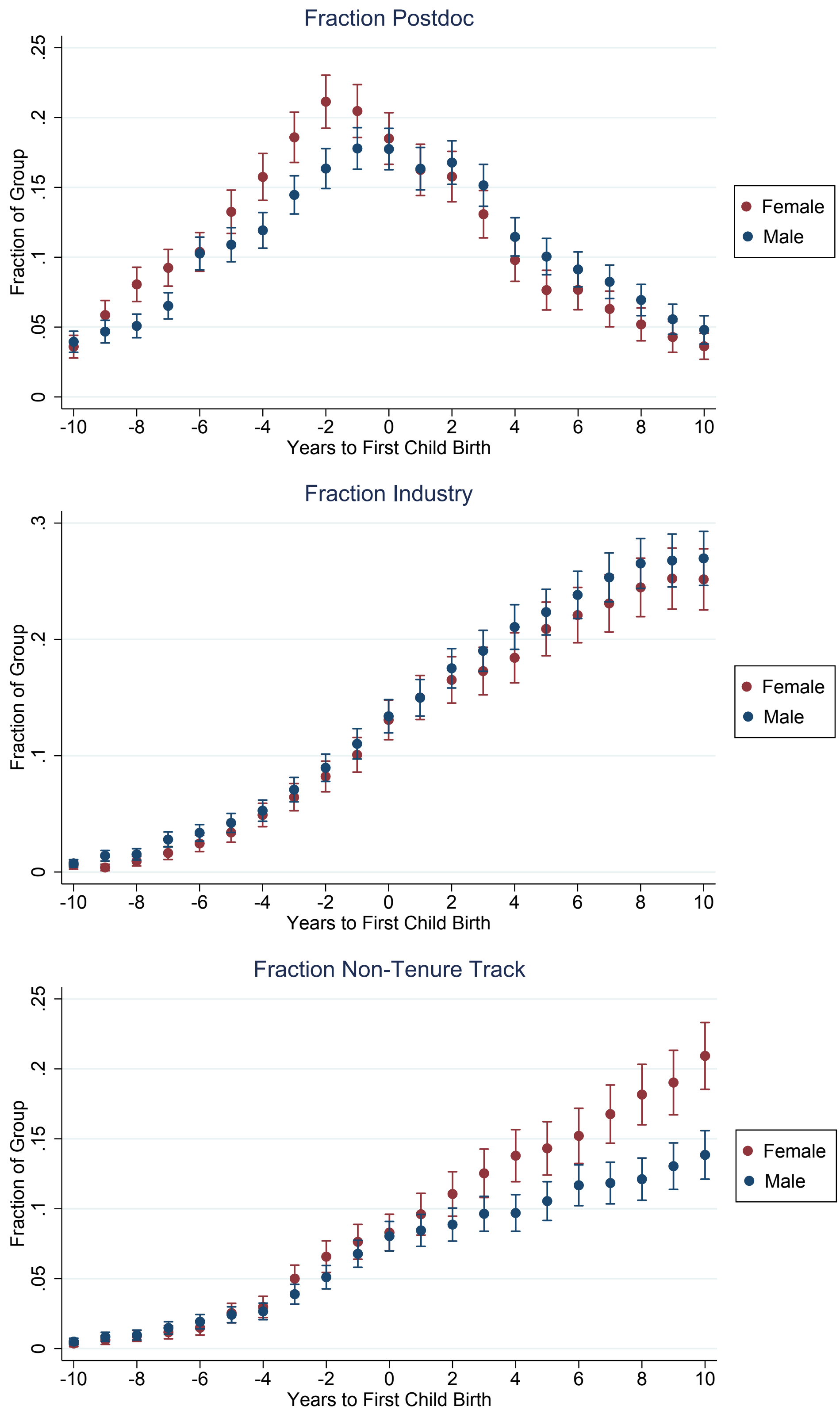
Notes: These graphs give the raw fraction of male and female biological science Ph.Ds. who never have children that are in tenure-track positions in the first ten years after their Ph.D. graduation.

Figure 3: Fraction in Tenure-Track Positions During First Ten Years Post-Ph.D. by Gender and Grouped by Timing of First Child



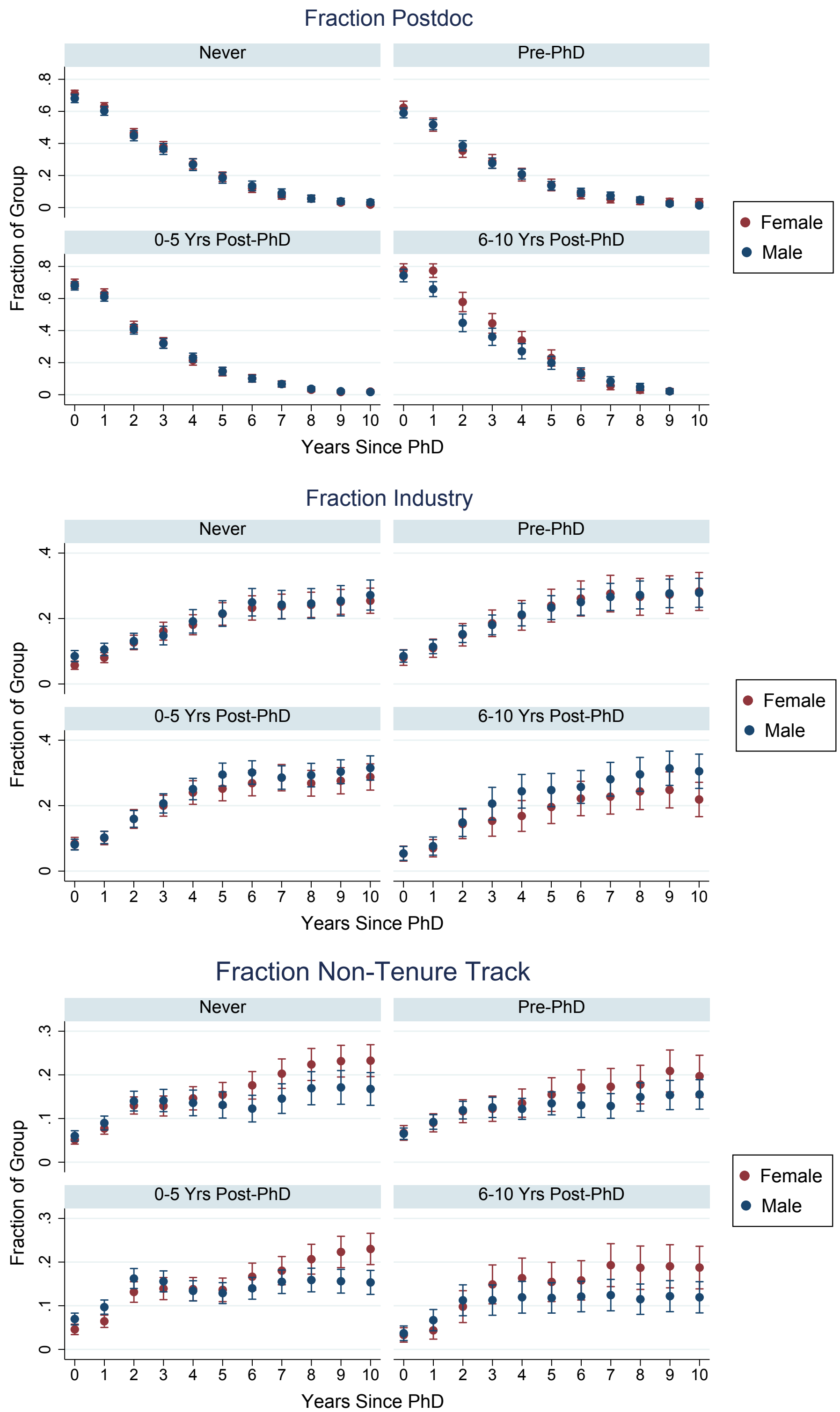
Notes: These graphs give the raw fraction of male and female biological science Ph.Ds. who have their first child before their Ph.D. graduation (top), in the first five years post-Ph.D. graduation (middle), or in six to ten years post-Ph.D. graduation (bottom) that are in tenure-track positions in the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

Figure 4: Fraction in Select Job Types Within Ten Years of First Child's Birth by Gender



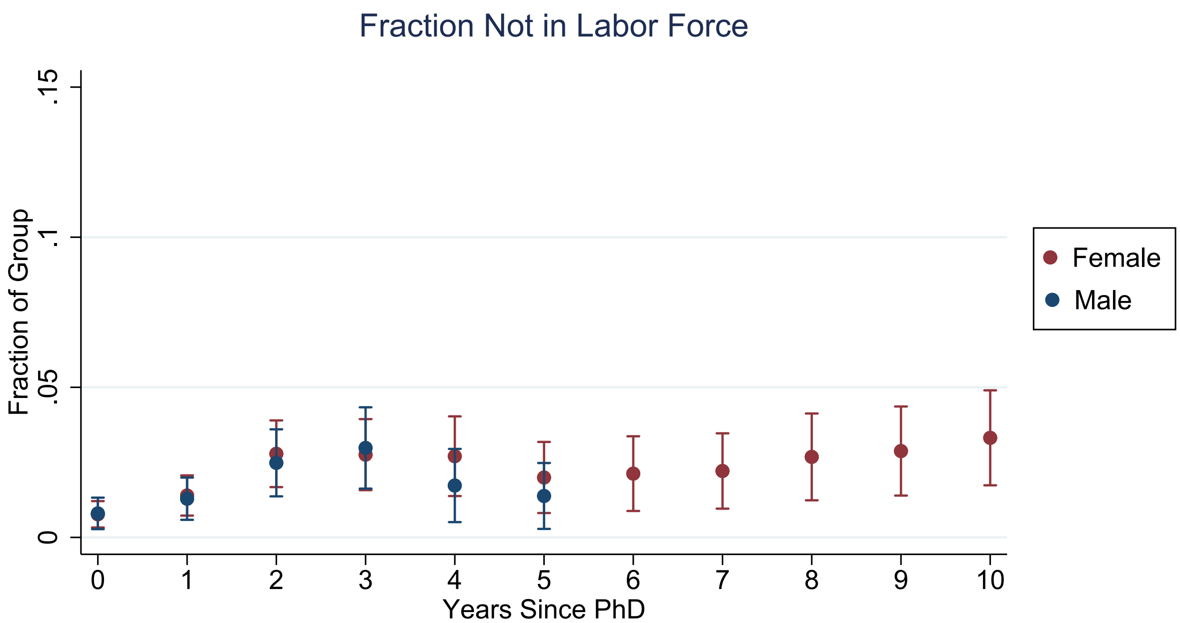
Notes: These graphs give the raw fraction of male and female biological science Ph.Ds. who become parents that are in postdoctoral (top), for-profit industry (middle), and non-tenure track academic (bottom) positions in the ten years before through the ten years after the birth of their first child.

Figure 5: Fraction in Select Job Types During First Ten Years Post-Ph.D. by Gender and Grouped by Timing of First Child



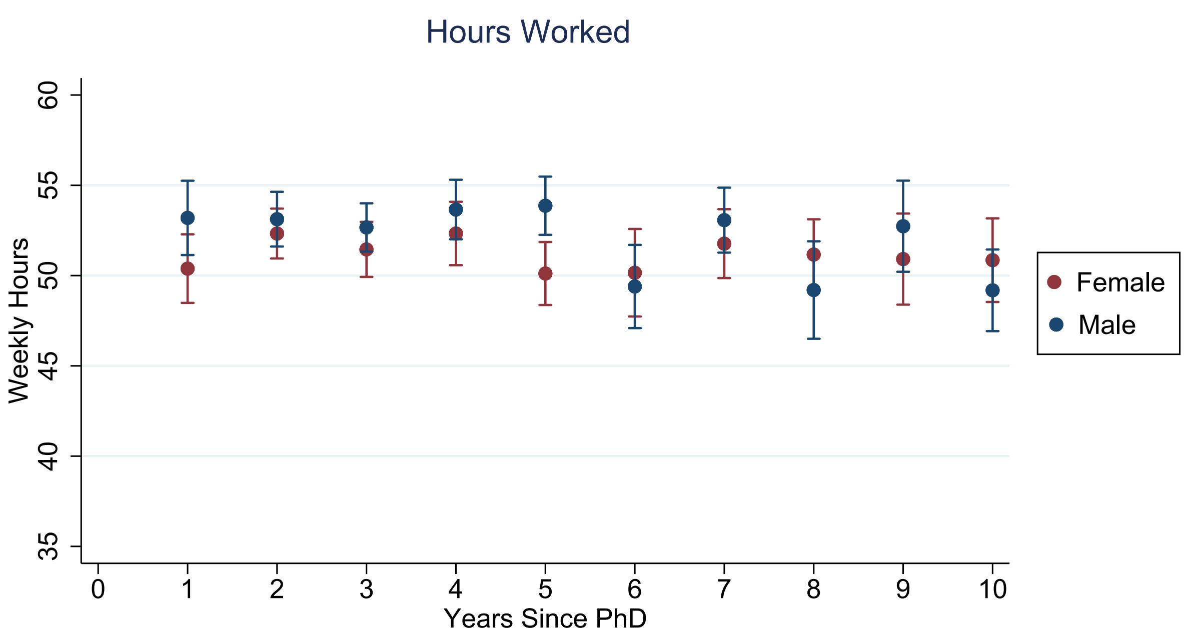
Notes: These graphs give the raw fraction of male and female biological science Ph.Ds. that are in postdoctoral (top), for-profit industry (middle), and non-tenure track academic (bottom) positions in first ten years after their Ph.D. graduation, grouped by whether they never have children (top left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

Figure 6: Fraction Out of Labor Force During First Ten Years Post-Ph.D. by Gender Among Ph.Ds. with No Children



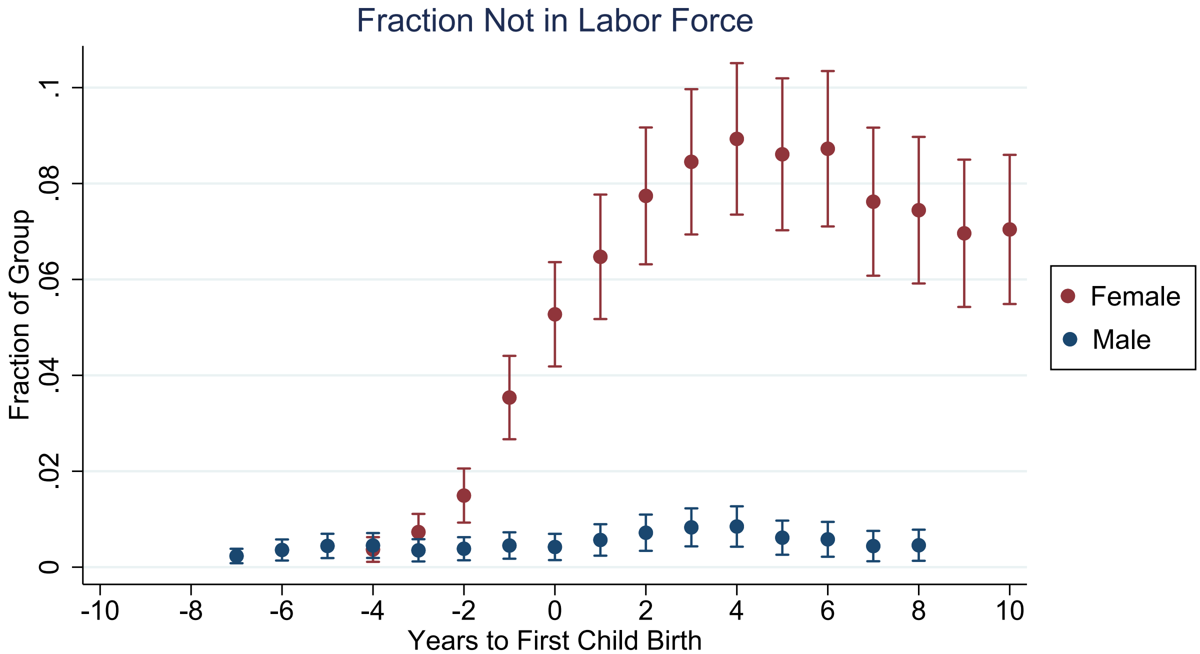
Notes: This graph give the fraction out of the labor force in the first ten years post-Ph.D. among male and female biological science Ph.Ds. who never have children. For disclosure purposes, only groups with at least fifty individuals and cells with at least five individuals are shown.

Figure 7: Average Hours Worked During First Ten Years Post-Ph.D. by Gender Among Ph.Ds. with No Children



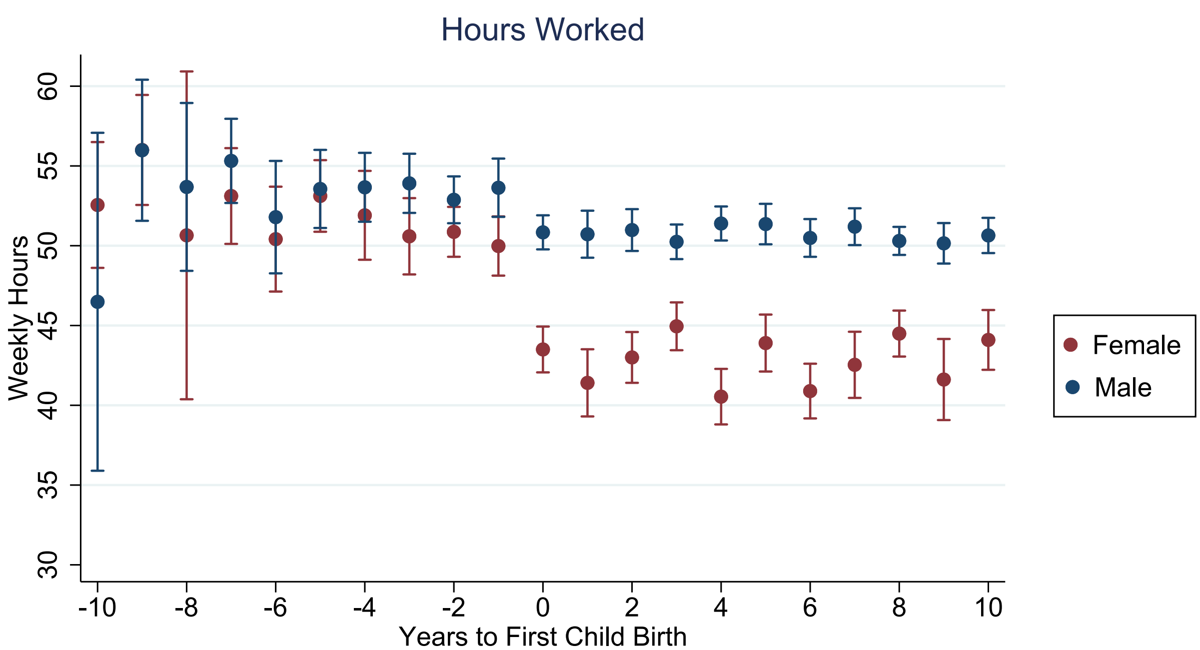
Notes: This graph give the fraction out of the labor force in the first ten years post-Ph.D. among working male and female biological science Ph.Ds. who never have children.

Figure 8: Fraction Out of Labor Force Within Ten Years of First Child's Birth by Gender



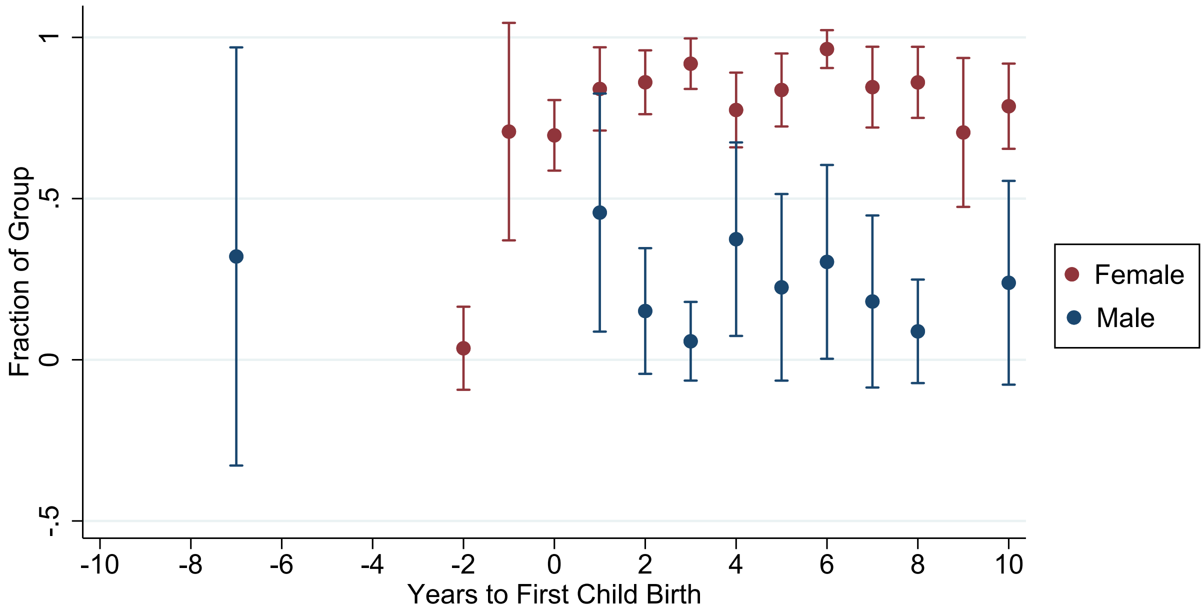
Notes: This graph give the fraction out of the labor force among male and female biological science Ph.D. parents in the ten years before through the ten years after the birth of their first child. For disclosure purposes, only groups with at least fifty individuals and cells with at least five individuals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

Figure 9: Average Hours Worked Within Ten Years of First Child's Birth by Gender



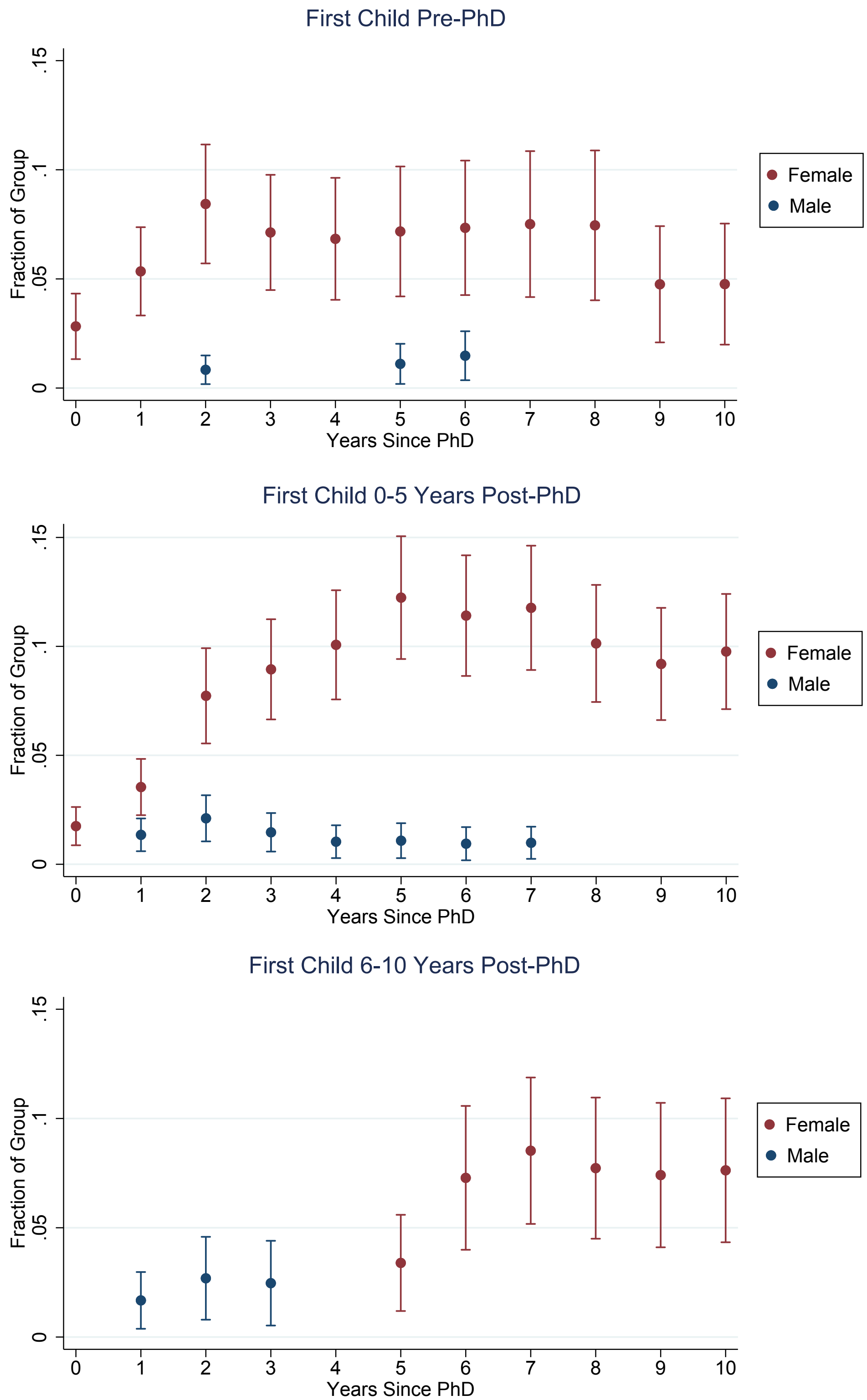
Notes: This graph give the average hours worked among working male and female biological science Ph.D. parents in the ten years before through the ten years after the birth of their first child.

Figure 10: Fraction that List Family-Related Reasons for Not Working Within Ten Years of First Child's Birth by Gender



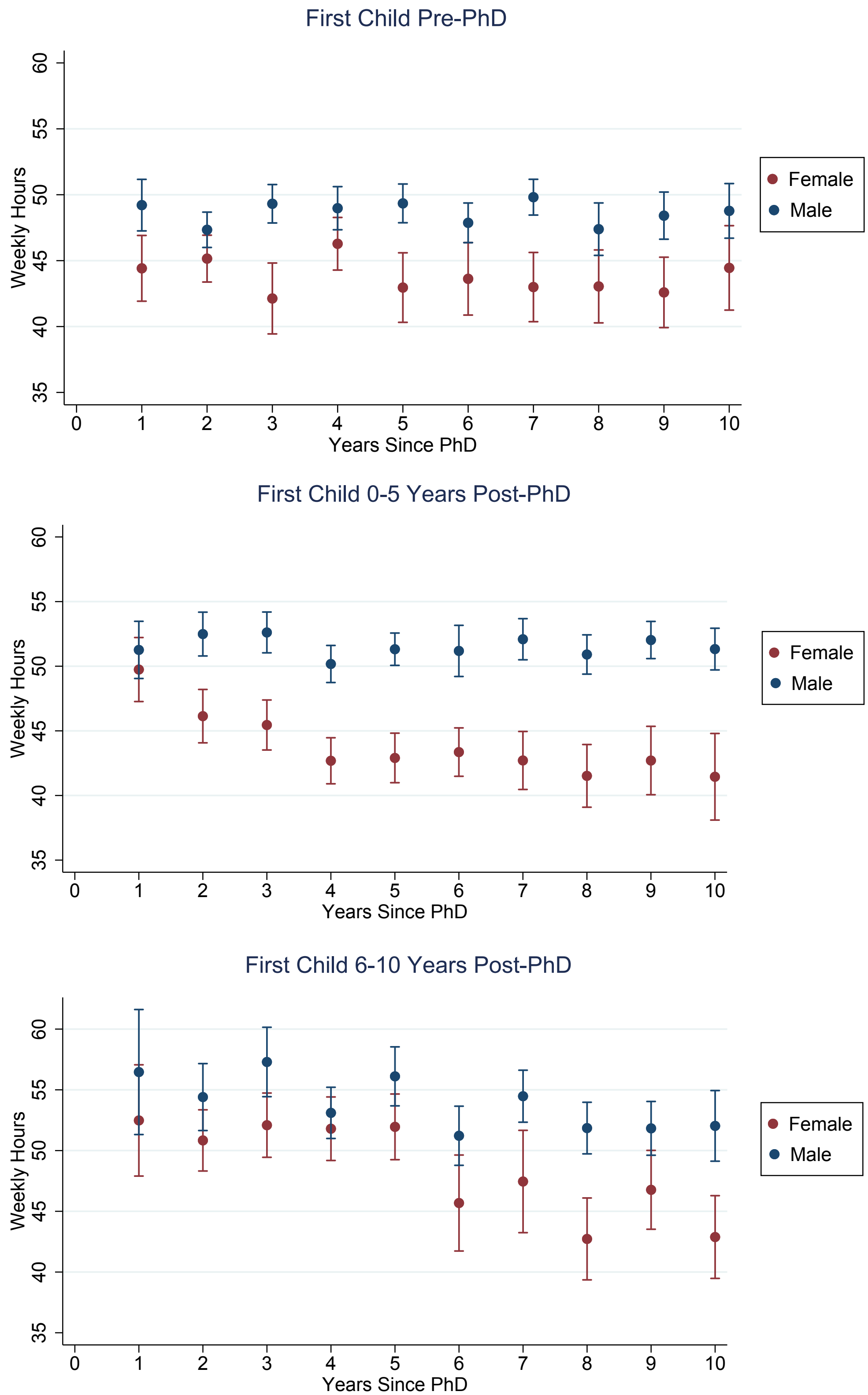
Notes: This graph give the percent of male and female biological science Ph.D. parents who list family-related reasons as a factor in their decision to not work in the ten years before through the ten years after the birth of their first child.

Figure 11: Fraction Out of Labor Force During First Ten Years Post-Ph.D. by Gender and Grouped by Timing of First Child



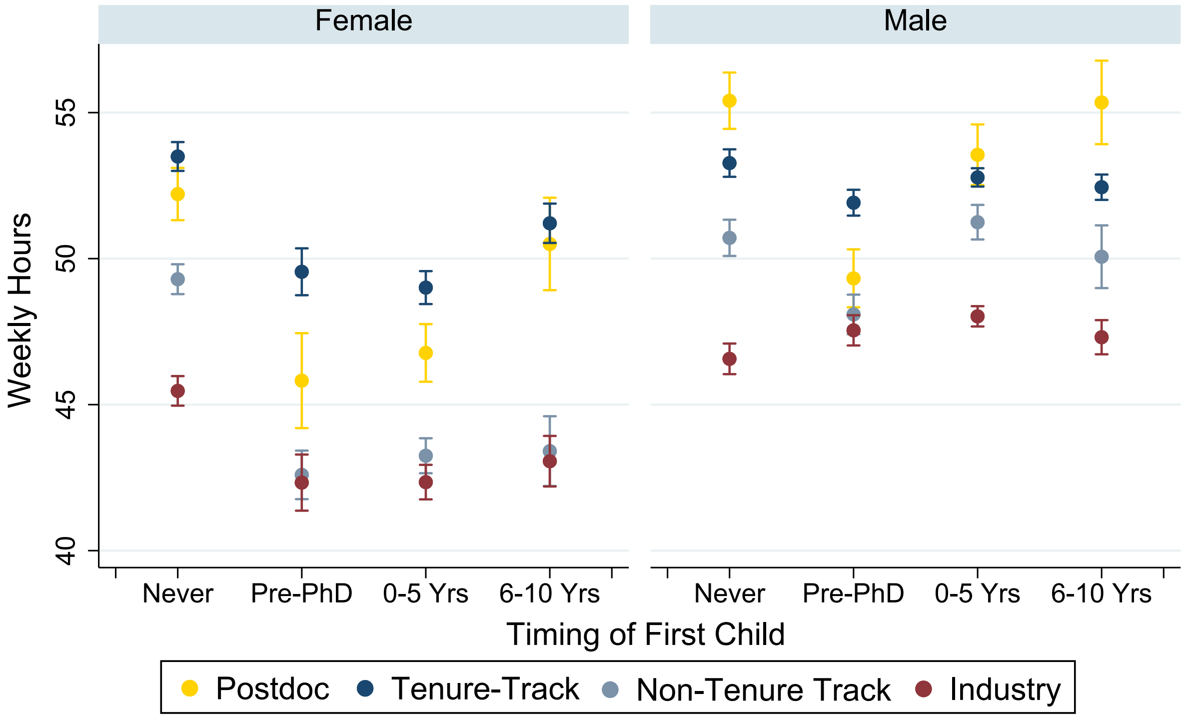
Notes: These graphs give the fraction out of the labor force in the first ten years post-Ph.D. among male and female biological science Ph.D. parents, grouped by whether have their first child before their Ph.D. graduation (top), in the first five years post-Ph.D. graduation (middle), or six to ten years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

Figure 12: Average Hours Worked During First Ten Years Post-Ph.D. by Gender and Grouped by Timing of First Child



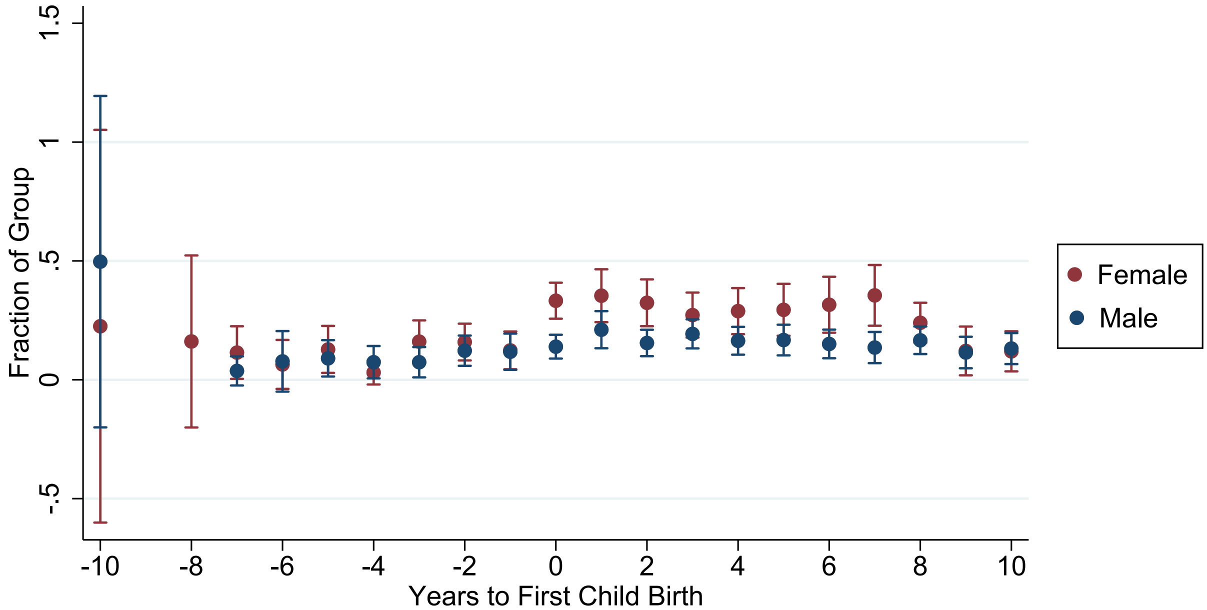
Notes: These graphs give the average hours worked in the first ten years post-Ph.D. among working male and female biological science Ph.D. parents, grouped by whether have their first child before their Ph.D. graduation (top), in the first five years post-Ph.D. graduation (middle), or six to ten years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

Figure 13: Select Job Types' Average Work Hours by Gender and Grouped by Timing of First Child



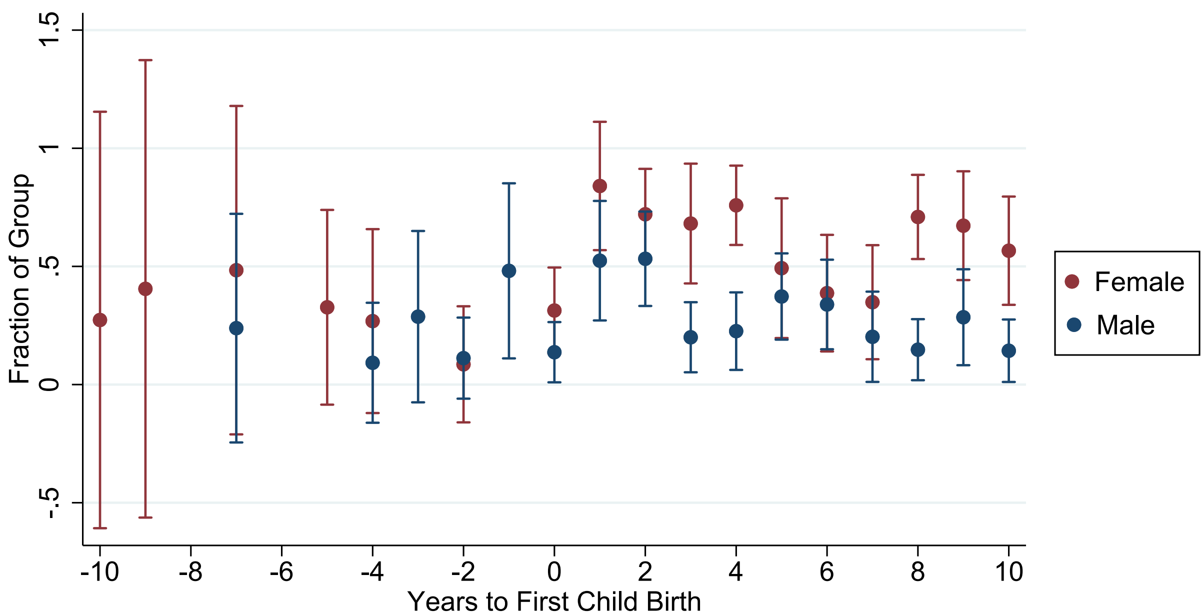
Notes: This graph gives the average hours worked in four select job types for male and female biological science Ph.Ds. employed in these positions, grouped by whether they never have children, have their first child before their Ph.D. graduation, have their first child in the first five years post-Ph.D.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

Figure 14: Fraction that List Family-Related Reasons for Changing Jobs Within Ten Years of First Child's Birth by Gender



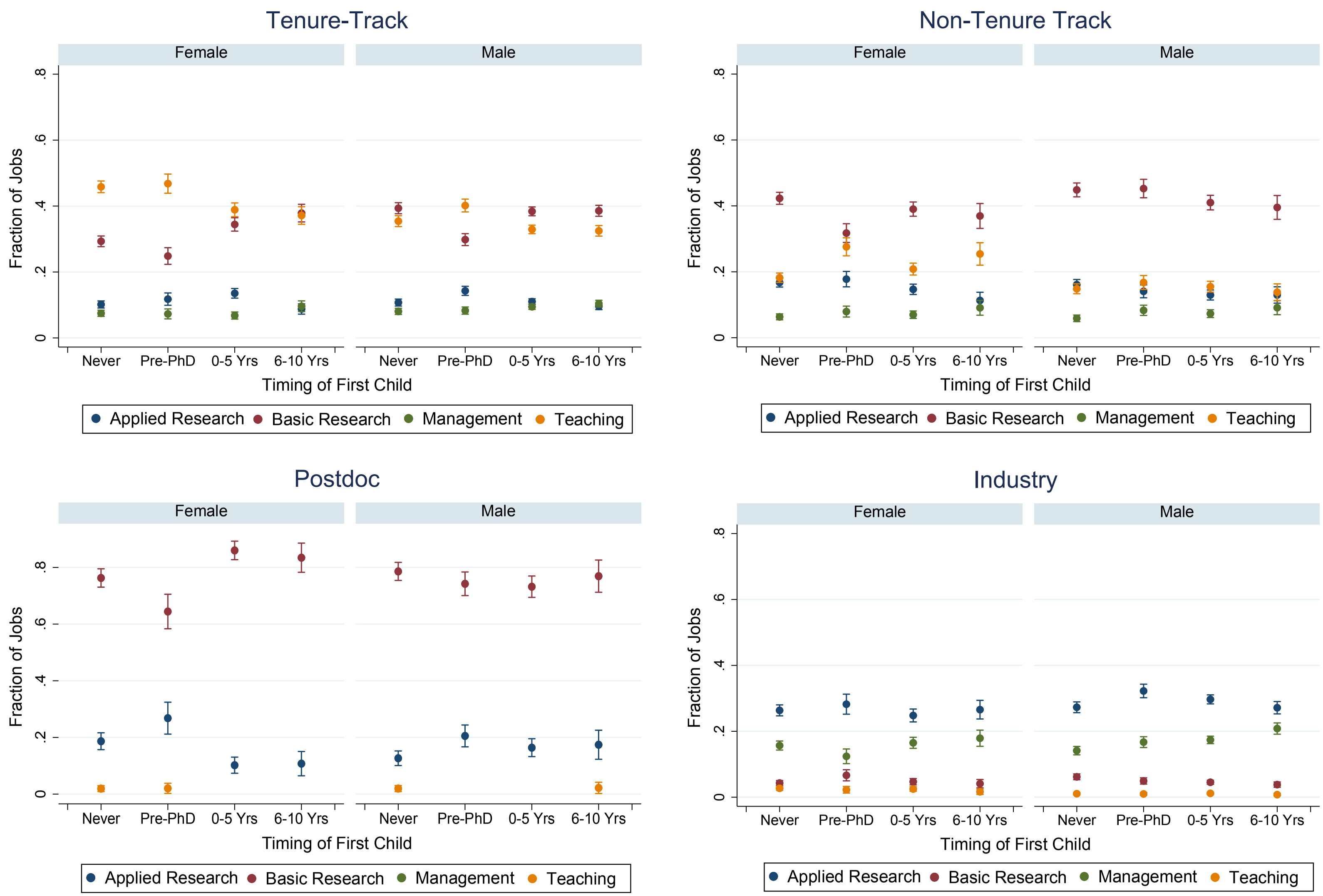
Notes: This graph give the percent of male and female biological science Ph.D. parents who list family-related reasons as a factor in their decision to change jobs in the ten years before through the ten years after the birth of their first child.

Figure 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



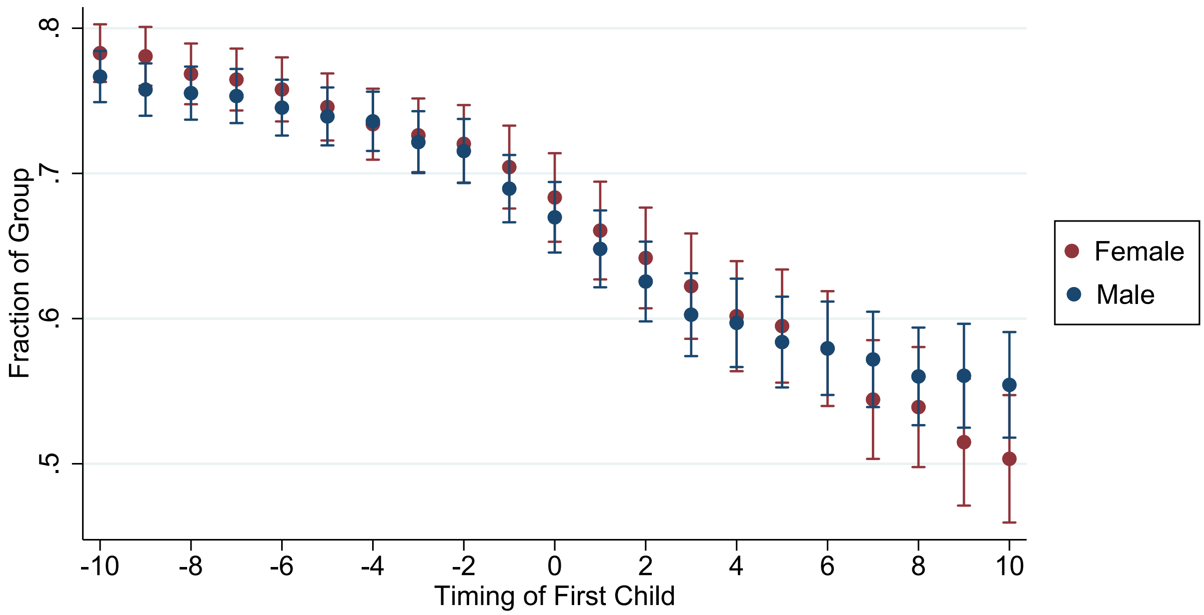
Notes: This graph give the percent of male and female biological science Ph.D. parents who list family-related reasons as a factor in their decision to work outside their Ph.D. field of study in the ten years before through the ten years after the birth of their first child.

Figure 16: Select Job Types' Most Hours Spent Work Activity by Gender and Grouped by Timing of First Child



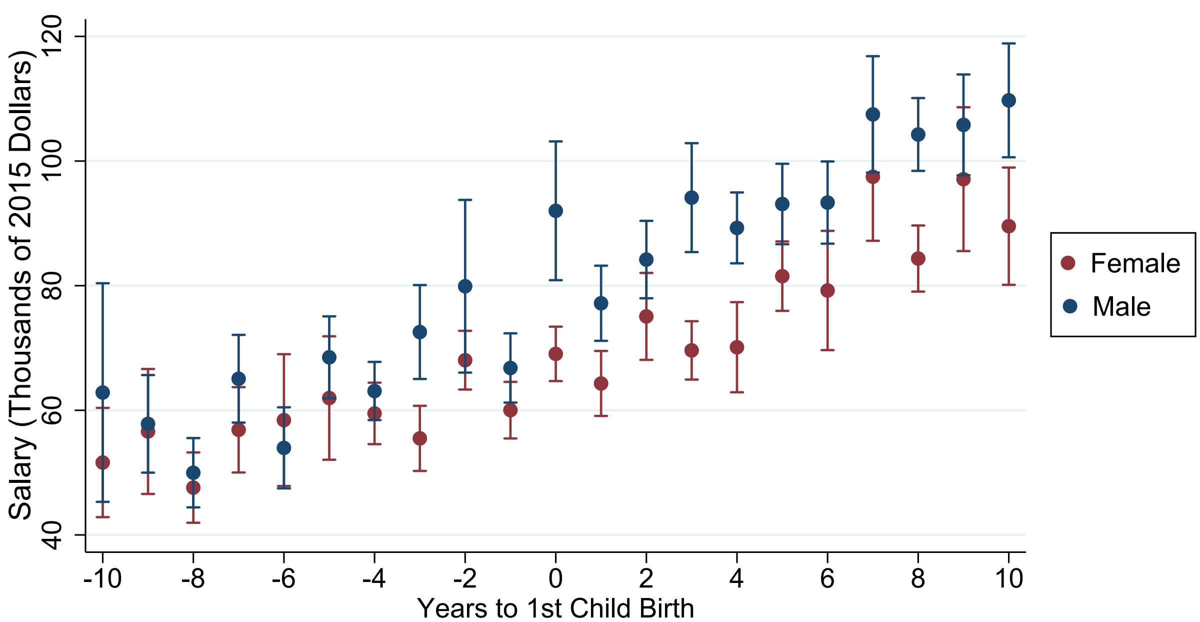
Notes: This graph gives the fraction of tenure-track academic (top left), non-tenure track academic (top right), postdoctoral (bottom left), and industry (bottom right) positions that spend their most hours on four select work activities for male and female biological science Ph.Ds. employed in these 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.

Figure 17: Fraction in Carnegie-Classified "High Research Activity" Institutions Within Ten Years of First Child's Birth by Gender



Notes: This graph gives the raw fraction in Carnegie-Classified "high research activitiy" institutions, conditional on being in any academic position (graduate student, postdoctoral researcher, tenure-track academic, 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.

Figure 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.

7 Tables

Table 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 an 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. 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. 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.

Table 2: Range of Estimated First Child's 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 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 possible birth years of first children.

Table 3: 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 (as measured by the Carnegie Classification system), 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 4: 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						
Postdoc	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						
Postdoc	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 5: 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 6: 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.

Table 7: 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.

Table 8: Logit Regressions of Job Type on Timing of First Child's Birth

	Pr(Postdoc) (1)	Pr(Tenure-Track) (2)	Pr(Non-Tenure Track) (3)	Pr(Industry) (4)	Pr(Not in Labor Force) (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), non-tenure track academic 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.

Table 9: 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.

Careers Versus Children:

How Childcare Affects the Academic Tenure-Track Gender Gap

Stephanie D. Cheng

Data Appendix

A Child Birth Years Algorithm

This appendix details the methodology used to identify an SDR individual's total number of children and estimate their children's birth years. It performs the methodology on the example individual Ph.D. whose child age bins across survey waves are given in Appendix Table A1. Note that this data has been constructed for example purposes and does not represent an actual individual in the SDR data.

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 A2). 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.

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 A3). 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%)

of the sample has fewer than five children. I keep the process to Ph.Ds. with fewer than five children to reduce computational time.

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 A4). 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 A1: Example Number of Child Age Bins for an Individual Ph.D. Across Survey Waves

Survey	Under 2	Ages 2-5	Under 6	Ages 6-11	Ages 12-17	Ages 18+	Ages 12-18	Ages 19+
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(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.

Table A2: Example Ticker System: # of a Ph.D.'s Children Passing Each Age Bin

Survey	Under 2	Ages 2-5	Under 6	Ages 6-11	Ages 12-17	Ages 18+	Ages 12-18	Ages 19+	Children Left	New Children	Total Children
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(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).

Table A3: Example Tickers Broken-Down Into Individual Child Indicators

Survey	Under 2	Ages 2-5	Under 6	Ages 6-11	Ages 12-17	Ages 18+	Ages 12-18	Ages 19+	Children Left
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(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.

Table A4: Example Estimation of Child Birth Years

	1st Child				2nd Child		
Survey	Age Bin	Start	End	Survey	Age Bin	Start	End
	(1)	(2)	(3)		(4)	(5)	(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	Start	End	Survey	Age Bin	Start	End
	(7)	(8)	(9)		(10)	(11)	(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.

B Tracking STEM Ph.D. Careers

B.1 Career Paths Construction

This appendix details the methodology used to identify an SED-SDR individual's career paths across six job types and two employment statuses. It performs the methodology on the example individual Ph.D. whose true career path is given in Appendix Table B1. Based on this true path, the individual fills out the job-related variables from each SED or SDR survey in Appendix Table B2. Note that this data has been constructed for example purposes and does not represent an actual individual in the SED-SDR data.

I start by identifying all individuals covered by the 1993-2015 SDR, matching to their SED responses using the variable *refid* and to 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 postdoc fellowship, a postdoc research associateship, a traineeship, or a clinical residency internship. In the SDR, the indicator for a postdoc 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 postdoc history (given by postdoc starting and ending years, *pd*syr* and *pd*eyr)*.

- **Tenure-Track Academic (TT):** In the SED, the individual's postgraduation plan is not a postdoc (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 postdoc but is either tenured or on the tenure track (as given by the variables *facten* and *tensta*).

- **Non-Tenure Track Academic (NT):** In the SED, the individual's postgraduation plan is not a postdoc 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 postdoc 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.D.s' 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,[29] comparison to their previous job,[30] and retrospective postdoctoral experience asked of respondents in 1995 and 2006.[31] 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:

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

[30]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.

[31]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*).

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. **Postdoc retrospective:** Individual stated they were in a postdoctoral position in the retrospective 1995 and 2006 data, as given by the postdoc start and end dates. Fill indicators for all 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 B3. 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. Appendix Table B4 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 B3, the example individual is considered to have spent four years as a postdoc, four and a half years as a tenure-track academic, 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 a postdoc 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.

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).

B.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.[32] 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, 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. For interpolation between survey years, I utilize the job indicators constructed in Appendix B.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.

[32] 3.60% of observations change marital status; 7.09% change having children living with them; and less than 1% change US citzenship or residency status between surveys.

Table B1: 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 shows the true career path of a constructed SDR individual. Column 1 gives the reference year, *refyr*. Columns 2-9 give job types, as abbreviated in Appendix B.1. A marked box denotes employment in that job type 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 postdoc position to another in 1991, so the first postdoc job is denoted by X and the second is denoted by Y.

Table B2: 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 B1. 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_ min*; 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.

Table B3: 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 shows the constructed career path based off the individual's SED and SDR survey responses in Table B2. Column 1 gives the reference year, *refyr*. Columns 2-9 give job types, as abbreviated in Appendix B.1. 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 B1.

Table B4: Percent of Job Indicators Determined by Step Hierarchy, STEM Sample

Step	*PD*	*TT*	*NT*	*ID*	*GV*	*NP*	*UN*	*NL*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1: New Job	21.76%	7.68%	13.30%	12.91%	10.10%	11.79%	32.79%	15.55%
2: Postdoc Retrospective	32.03%							
3: Current Job	15.44%	85.96%	80.16%	78.57%	79.16%	76.08%	64.16%	83.71%
4: Same Job, Same Employer	0.24%	0.15%	0.67%	0.31%	0.28%	0.30%		
4.1: Same Job, Diff Employer	0.79%	0.39%	1.04%	1.06%	0.63%	1.16%		
4.2: Diff Job, Same Employer	1.42%	2.08%	2.11%	2.80%	2.71%	2.27%		
5: Expected Post-Grad Job	18.74%	2.77%	1.43%	2.39%	5.02%	6.07%		
6: No Info, Expect Transition	9.58%	0.97%	1.31%	1.95%	2.10%	2.34%	3.05%	0.74%
Number of Observations	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: 1) PD: postdoctoral researcher, 2) TT: tenure-track academic, 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.

C NSF SED-SDR Fields of Study

Table C1 gives the distribution of first-time Ph.D. fields for SED-SDR respondents. This paper focuses on the biological/biomedical sciences, which represent the largest STEM field and the largest number of female research doctorate holders.

Table C1: Distribution of SED-SDR Ph.D. Fields of Study

Ph.D. Field of Study	*Percent of Sample* (1)	*Percent Female* (2)
Agricultural Sciences/Natural Resources	4.23%	23.4%
Biological/Biomedical Sciences	20.53%	38.4%
Chemistry	9.09%	22.7%
Computer & Information Sciences	2.48%	17.4%
Economics	2.87%	-
Education	0.71%	-
Engineering	18.92%	12.9%
Health Sciences	4.40%	61.5%
Humanities	0.55%	-
Mathematics	4.35%	20.3%
Physics	5.44%	10.6%
Professional Fields	0.11%	-
Psychology	13.14%	54.2%
Other Physical Sciences	3.33%	20.8%
Other Social Sciences	9.72%	-
Number of Individuals	124,658	

Notes: This table describes the distribution of Ph.D. fields of study; the SED-SDR allows respondents to choose from over 700 fields to describe their program, which the NSF groups into the 15 general fields listed in this table. Column 1 gives the percentage of the full SED-SDR sample that receive their first doctorate in each general field of study. Column 2 gives the percent female within each STEM general field of study.

As defined by the NSF, biological/biomedical sciences compose the following fields of study: anatomy, bacteriology, biochemistry, bioinformatics, biomedical sciences, biometrics & biostatistics, biophysics, biotechnology, botany/plant biology, cancer biology, cell/cellular biology & histology, computational biology, developmental biology/embryology, ecology, endocrinology, entomology, environmental toxicology, epidemiology, evolutionary biology, human & animal genetics/genomics, immunology, microbiology, molecular biology, molecular medicine, neurosciences & neurobiology, nutrition sciences, parasitology, human & animal pathology, human & animal pharmacology, human & animal physiology, plant genetics, plant pathology/phytopathology, plant physiology, structural biology, toxicology, virology, wildlife biology, zoology, general biology/biomedical sciences, other biology/biomedical sciences.