# WOMEN IN SCIENCE
# LESSONS FROM THE BABY BOOM

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How do children affect women in science? We investigate this question using rich biographical data, linked with patents and publications, for 83,000 American scientists in 1956 at the height of the baby boom. Our analyses reveal a unique life-cycle pattern of productivity for mothers. While other scientists peak in their mid-thirties, mothers become more productive after age 35 and maintain high productivity in their 40s and 50s. Event studies show that the output of mothers increases after 15 years of marriage, while other scientists peak in the first 10 years. Differences in the timing of productivity have important implications for tenure and participation. Just 27% of mothers who are academic scientists get tenure, compared with 48% of fathers and 46% of women without children. Mothers face comparable tenure rates to other assistant professors for the first six years but fall behind afterwards, suggesting that they face higher standards of early productivity. Mothers who survive in science are extremely positively selected: Compared with other married women, mothers patent (publish) 2.5 (1.4) times more before the median age at marriage. Compared with men, female scientists are more educated, half as likely to marry, one-third as likely to have children, but half as likely to survive in science. Employment records indicate that a generation of baby boom mothers was lost to science.

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Women continue to be underrepresented in science, especially at the top levels of executives and tenured professors. In the United States, women account for just 34% of full professors, in Canada 28%, in the UK 26%, and in Germany 19% (Catalyst 2020).[1] Some of the persistent scarcity may be due to structural impediments, including discrimination at hire, glass ceilings in promotion, inequities in salary and support (Sonnert and Holton 1996, Altonji and Blank 1999), and a lack of role models among faculty (Carrell, Page, and West 2010, Porter and Serra 2020).

Children are another possible cause for the persistent underrepresentation of women in science. According to the American Time Use Survey, mothers spend roughly 50% more time caring for children than fathers even today (US Bureau of Labor Statistics 2020). During the COVID-19 pandemic, mothers with young children reduced their work hours between two to four times as much as fathers (Deryugina, Shurchkov, and Stearns 2021; Myers et al. 2020). While the long-run effects of this change are difficult to predict, high returns to labor market experience imply that reductions in work hours will harm the careers of mothers for many years (e.g., Alon et al. 2020). A rich existing literature has documented gender differences in the impact of children on earnings (e.g., Lundberg and Rose 2000, Bertrand, Goldin, and Katz 2010, Adda, Dustmann, and Stevens 2017, and Klevens, Landais, and Søgaard 2019), but the effects of children on *productivity* are less well understood.

This paper first investigates how children influence productivity, and more specifically the timing of productivity across the life cycle. Then, we examine how differences in the timing of productivity influence tenure and participation. Finally, we investigate selection: who becomes a parent, what types of research do they pursue, and who is more likely to survive in science? To perform these analyses, we collect rich biographical data on employment, education, marriage, and children for 82,094 male and female scientists from the *American Men of Science* (MoS 1956). The historical setting is the baby boom (1946-64) when couples had children soon after they married, and the burden of childcare fell squarely on women. Linking scientists with their patents and publications allows us to examine the impact of children on individual-level productivity over the life cycle, across demographic groups, and after marriage.

[1] Since the late 1980s, national committees and professional organizations have initiated programs to increase female participation in science and engineering hoping that increasing the talent pool will lead to more women in STEM (Chesler and Chesler 2002). Yet, these programs have not led to a proportional increase in women faculty (Barber 1995, Kulis et al. 2002, Nelson and Rogers 2004, NSF 2003, and Pell 1996).

Matched patent data show that the productivity of mothers increases after age 35, while other scientists peak in their mid-30s. Inventions by mothers increase up to age 27 (the median age of marriage) and flatten afterwards, while fathers become more productive after marriage. After the age of 35, mothers invent more while other scientists invent less. While other scientists decline in their 40s, mothers are prolific, creating 70.4 additional patents per 1,000 scientists at age 42 compared with themselves at age 20 and 61.3 additional patents at age 46.

Comparisons of patenting across demographic groups suggest that mothers are more productive than other women, possibly due to selection. Overall, however, women patent significantly less than men, and only a small share of scientist-inventors (less than 1%) are women, extending findings for recent data (e.g., Bell et al. 2019). Consistent with earlier research documenting higher earnings for fathers (e.g., Bertrand, Goldin, and Katz 2010), we also find that fathers produce more patents than other men. Intensity estimates show that fathers patent more with each child, which suggests that children encourage fathers to specialize in work that increases family income.

To investigate the causal effects of children on productivity, we estimate event studies of changes in patenting after marriage separately for mothers, fathers, other women, and other men. Methodologically, the event study approach exploits the fact that changes in productivity due to the birth of a child occur sharply, while other determinants of productivity, such as a person's preference for leisure, influence productivity more smoothly. Another benefit of the event study approach is that it allows us to exploit the long-run nature of our scientist-level productivity data and document changes in productivity across the entire life cycle of a scientist.

Event study estimates reveal a large and persistent increase in the productivity of mothers 15 years after marriage. Matching our scientists with census data, we find that most scientists had their first child within three years of marriage. Children born within the first three or five years of marriage would be ten or older and require less work. The striking productivity increase after 15 years of marriage is unique to mothers. Fathers and other men patent more during the first 10 years of marriage but decline steadily afterwards, while patents by other married women remain relatively flat after marriage.

Analyses of publications confirm the unique life cycle patterns of productivity for mothers. Mirroring the upward trend for fathers, publications by mothers increase until the median age at marriage at 27. After marriage, however, publications by mothers increase at a lower rate and even decline, while publications by fathers continue to increase. Like patents, publications by mothers recover in their mid-30s. Publications remain high through their 50s, showing an even more persistent late-in-life increase than patents. At the age of 45 mothers publish 17.9 additional papers per 100 scientists compared with themselves at age 20; at the age of 60, mothers publish 18.2 additional papers, while fathers publish just 14.9 more.

These life-cycle differences in productivity have important implications for tenure and participation: Children explain nearly the entire gender difference in tenure rates for academic scientists. Only 27% of mothers who are academic scientists get tenure, compared with 48% of fathers and 46% of other women. Moreover, mothers are much less likely to get tenure track positions, and they wait longer for these jobs.

Changes in tenure rates per year suggest that mothers are held to higher standards of early productivity. Starting from their first year as assistant professors, tenure rates for mothers and other scientists are comparable for the first six years. After year six, however, tenure rates for mothers flatten while those for fathers continue to increase. Fifteen years after starting as assistant professors, 62% of fathers and 54% of other women have tenure compared with just 38% of mothers. Notably, married women without children also fall behind after six years but catch up as they get older and their risk of motherhood declines. Tenure decisions use past productivity to predict future productivity. If these bets are unbiased, changes in productivity after tenure should be comparable across demographic groups. Yet, mothers publish more after tenure, while the productivity of fathers and other men increases up to tenure and flattens afterwards. These differences point to structural forces in the tenure process that disadvantage mothers.

Mothers who survive in science are extremely positively selected. By age 27 (the median age of marriage), mothers produce 5.5 times as many patents compared with single women and 2.4 times as many compared with other married women. Mothers also publish 1.3 times as much before marriage compared with both single and other married women. By comparison, fathers seem less positively selected, especially in terms of publications. Fathers produce 1.2 and 1.3 times as many patents before marriage compared with single and other married men respectively, but they do not publish more than single or other married men. These results suggest that fathers are more positively selected in terms of patents (which generate earnings, Kline et al 2019), but not in terms of publications.

Internalizing the career costs of children, female scientists are one-third as likely to have children compared with men, and half as likely to marry. Matching pre-baby boom faculty directories with the MoS, we find that women were half as likely to survive in science compared with men. These demographic differences in survival led to a major loss in participation for the generation of baby boom mothers. Among women born between 1916 and 1925, who were in their 20s at the beginning of the baby boom, just 923 were recorded as active scientists in the MoS (1956), compared with 1,118 and 1,043 women born in the preceding decades. Comparing participation across cohorts, we estimate that almost 180 female scientists – the missing mothers of the baby boom – were lost to American science.

In the final section of the paper, we examine access to childcare as a potential tool to mitigate the career costs of children. To perform this analysis, we match faculty members with the US Census of 1940, which includes information on earnings and live-in servants. While the number of matched women is small because women faculty are scarce and women are exceedingly difficult to match with census records (e.g., Feigenbaum 2016), matched records indicate that mothers who had access to childcare were more likely to survive in science.

Our results speak to the forces driving lower rates of promotion and persistent underrepresentation of women in science (e.g., National Academy of Science 2006). In economics, female scholars are less likely to be promoted (McDowell et al. 1999) and co-authorships reduce tenure rates for women but not men (Sarsons et al. 2021). In STEM, women have shorter careers and are more likely to stop publishing (Huang et al. 2020). Text analyses of publications in science, technology, engineering, mathematics, and medicine (STEMM) indicate that research fields such as surgery, computer science, physics, and mathematics will not approach gender parity in the 21st century (Holman et al. 2018). Models of economic growth attribute up to 25% of growth since 1960 to the reduced barriers for women and minorities in education, training, and employment (Jones et al. 2019). Yet, women continue to face extremely unfavorable odds in patenting (Jensen et al. 2018, Bell et al. 2019). Our research suggests that the unequal burden of children is a major barrier facing female inventors.

During the COVID pandemic, parents of both genders have lost research time, but mothers have lost twice as much (one hour per day) compared with fathers (Deryugina, Shurchkov, and Stearns 2021). Survey data suggest that female scientists with young children have suffered the most dramatic decline in research time (Myers et al. 2020). Female scientists reported a 5% larger decline in research time compared with men, and scientists with children below the age 6 experienced a 17% larger decline in research time compared with scientists with older children. While the long-run effects of this shock are difficult to predict, our findings imply large and persistent long-run effects on productivity, promotions, and participation.

Our findings also contribute to understanding the role of productivity as a driver of child penalties in earnings. Analyses of registry data for Denmark between 1980 and 2013 show that children reduce the earnings of women by 20% relative to men (Klevens, Landais, and Søgaard 2019). For MBA graduates, nearly half of the earnings deficit for women can be explained by reduced weekly hours and non-work spells for mothers (Bertrand, Goldin, and Katz 2010, p. 241). Data on gender differences in the willingness to commute show that gender differences in the willingness to commute are larger for people with children (24%) than for singles (8%), which suggests that mothers have fewer hours available to spend on work outside the home (Le Barbanchon, Rathelot, and Roulet 2021). To this literature we add evidence on the effects of children on the timing of productivity and implications for promotions and participation.

The historical setting of the baby boom is interesting in several dimensions. First, at the time of the baby boom, the burden of childcare fell squarely on mothers, allowing us to examine an extreme case when mothers do all the work. Second, the setting allows us to investigate the effects of parenting before the introduction of oral contraceptives, also known as the "pill." Previous research has linked advances in gender equality since the 1950s to the ability to delay having children. Using variation in legal access within cohorts and across states, Goldin and Katz (2002) show that access to the pill altered the career paths of young unmarried women and increased their age at first marriage. Bailey (2006) shows that legal access to the pill before the age of 21 reduced the likelihood of a first birth by the age of 22, increased female labor force participation, and raised the number of annual hours worked. Our findings complement this research by documenting the career costs of children for highly educated women before the pill.

## I. Historical Background

After World War II, more Americans than ever married, married early, had children, and stayed married. In 1930, the median woman had first married at age 21.3; by 1950, the median age of marriage had dropped by a full year to 20.3 (U.S. Census 2020). In 1960, only 27.4% of women between the age of 20 and 24 were single. Divorce rates slowed to a low point of 8.9 per 1,000 women aged 15 and older in 1958. The combination of these factors led to a dramatic increase in births from 1946 to 1964, during the "baby boom" (Appendix Figure A2).[2] Between 1940 and 1947, annual births increased from just 19.4 per 1,000 people in 1940 to 26.6 in 1947. Ten years later, in 1957, 25.3 children per 1,000 people were born in the United States. Women "bore and raised children in their early twenties," creating a "collapsed period of intensive child rearing" and a "relative freedom from such demands" when they reached their late thirties and early forties (Weiss 2020, p.8). Couples also had children more quickly after they married and spaced their children closely together (Weiss 2020, p. 4).

During this time, the burden of childcare fell squarely on mothers, and women were expected to focus their attention on the home. Some have argued that preferences explain the underrepresentation of women in science. Kevles (1995, 1st ed. 1971, p.371) writes "Women generally preferred to find their own primary fulfillment as mothers of accomplished children and wives of prominent husbands. On the whole, women of the postwar era went to work to help raise the family standard of living; they had jobs, not careers."[3] Institutional barriers further discouraged the participation of women in academia and industry. Prohibitions against the employment of married women ("marriage bars") were widespread in the early decades of the 20th century. At their height, marriage bars affected 87% of school districts and about 50% of office workers (Goldin 1990, pp.160-61). Later, marriage bars morphed into hiring policies that excluded pregnant women and mothers of young children. In addition, "nepotism rules" barred spouses of university scientists to work at the same institution (Goldin 2021, p.3).

## II. Biographies Linked with Patents and Publications

To examine how children affect productivity, we link the biographies of 82,094 American scientists with their patents and publications. Data include the scientist's birth year, gender, education, employment, promotions, marriage, and children, along with scientific output.

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[2] There are many competing explanations for the causes of the baby boom. For example, Doepke, Hazan, and Moaz (2015) argue that competition with women who entered the labor force during WWII and stayed in the labor force after the war, made it harder for younger women to get jobs, encouraging them to exit the labor market and have children. There is, however, an active debate on whether women who entered the labor force during the war remained in the labor force after the war (e.g., Goldin 1991 and Rose 2018).

[3] While such preferences are persistent (Alesina, Giuliano, and Nunn 2013), they are not immutable. Bursztyn, Gonzales, and Yanagizawa-Drott (2020), for instance, show that most young married men in Saudia Arabia privately support women working outside the home and underestimate support by other men like them. Correcting these beliefs increases men's willingness to help their wives look for jobs.

*2.1. Birth Years, Gender, Marriage, and Children for 82,094 Scientists*

For the main data, we have hand-collected rich biographical data for 82,094 scientists from the *American Men of Science* (MoS 1956). These data include 41,096 scientists in the physical sciences (STEM volume 1 of the MoS 1956), 25,505 in the biological sciences (volume 2), and 15,493 in the social sciences (volume 3).[4]

Originally collected by James McKeen Cattell (1860-1944), the "chief service" of the MoS was to "make men of science acquainted with one another and with one another's work" (Cattell 1921). Cattell was the first US professor of psychology and served as the first editor of *Science* for 50 years. In the MoS, he used this expertise to establish a compendium of scientists for his own research. Cattell published the first edition of the MoS in 1907, updating it until he passed the baton to his son Jacques who published the 1956 edition. Despite the name, the MoS includes both male and female scientists in Canada and the United States.

Entries in the MoS (1956) were subject to comprehensive input and review from "scientific societies, universities, colleges, and industrial laboratories." Jacques Cattell thanks these organizations for having "assisted in supplying the names of those whom they regard as having the attainments required for inclusion in the Directory." He also thanks "thousands of scientific men who have contributed names and information about those working in science," and "acknowledges the willing counsel of a special joint committee of the American Association for the Advancement of Science and the National Academy of Science National Research Council "which acted in an advisory capacity" (Cattell 1956, editor's preface).

To identify women, we use historical gender frequencies of first names in the US Social Security Administration Records (SSA) between 1880 and 2011. This approach performs best in predicting the gender of scientists who attended women's colleges (Data Appendix A). Among 82,094 American scientists, 4,220 (5.1%) are women, 66,560 (81.1%) are men, and 11,314 (13.8%) have unknown gender. The main specifications exclude scientists of unknown gender; robustness checks assign them to be female scientists.

Data on birth dates allow us to investigate changes in productivity across the life cycle. We also use birth years to control for cohort fixed effects. In addition, data on birth years improve the accuracy of matching scientists with patents, publications, and individual records in

[4] This count excludes 6,352 duplicate entries who appear in more than one of the three volumes of the MoS (1956), as well as 2,549 scientists whose entry consists only of a reference to another edition of the MoS.

the US census. Birth years are available for 99.2% of 82,094 American scientists in 1956, including 4,032 female scientists (95.6%) and 66,190 male scientists (99.5%).

A key feature of the MoS is that it records the scientist's year of marriage and the number of children they had by 1956. The chemist Giuliana Tesoro, for example, married in 1943 and had two children; this is recorded by "m. 43; c. 2" in Tesoro's entry in the MoS:

> TESORO, Dr. GIULIANA C, 278 Clinton Ave. Dobbs Ferry, N.Y. ORGANIC CHEMISTRY. Venice, Italy, June 1 21, nat. 46; m. 43; c. 2. Ph.D. (org. chem), Yale 43. Research chemist, Calco Chem. Co. N.J., 43-44; ONYX OIL & CHEM. CO, 44-46, HEAD ORG. SYNTHESIS DEPT. 46 – Chem. Soc; N.Y. Acad. Synthesis of pharmaceuticals, textile chemicals, germicides and insecticides; synthesis and rearrangement of glycols in the hydrogenated naphthalene series.

Matched census data (described in section 2.4) suggests that scientists typically had their first child within three years of marriage. Hand-matching men and women to the most recently available census in 1940, we find that scientists in this older cohort had their first child within 2.93 years of marriage (with a median of 3 years).[5] An alternative estimate for 9,101 fathers in the MoS (matched with the 1940 census through a machine-learning algorithm) confirms this estimate. Fathers in the MoS had their first child within 3.06 years of marriage (with a median of 3 years). Since older cohorts waited longer to have children (e.g., Goldin 2021), three years are probably an upper bound estimate for the birth of the first child.

### *2.1.1. Education, Academic and Industry Employment, Tenure, and Research Fields*

Data on university education allow us to calculate the share of scientists with PhDs, as well as the time they took to complete their PhDs and to get a tenure track job. These data are available for 99.7% of 4,032 female scientists and 99.4% of 66,198 male scientists.

Collecting data on job titles from the MoS allows us to examine promotions to tenure and to distinguish academics from industry scientists. *Academic scientists* are scientists who worked in an academic position at least once in their career, including assistant professor, associate professor, professor, research fellow, instructor, visiting professor, clinical professor, adjunct professor, professor emeritus, or dean. 3,537 (87.7%) female and 49,409 (74.6%) male scientists are academic scientists. Non-academic (*industry*) scientists are scientists who never held an

[5] Hand-matched census data include 131 scientists in the MoS (1956) who served on the faculty of Columbia University in 1943-45. With a median and average birth year of 1897, these scientists were roughly 15 years older than most scientists in the MoS (with a median birth year of 1912 and an average of 1909).

academic job. In analyses of patents, we examine inventions for both industry and academic scientists, while analyses of publications and tenure focus on academic scientists. Academic scientists with *tenure* are scientists who attain the rank of associate professor or professor.

Implementing a *k*-means matching methodology from Moser and San (2021), we use the text describing the disciplines and research topics to assign each scientist to a unique research field. This approach, which allows us to investigate selection into fields (e.g., Goldin 2014, Goldin and Katz 2016) and to control for differences in the propensity to patent or publish across fields (e.g., Moser 2012), offers several advantages over using disciplines alone. First, definitions of disciplines, such as “chemistry” are too broad to be useful. 7,091 alone scientists report their discipline as “chemistry” and 4,883 list physics; these definitions include scientists whose research has little overlap. On the opposite extreme, 384 scientists within the physical sciences define their discipline so narrowly that they are the only person in it; another 119 disciplines have just two people. Second, classifications by discipline may miss significant overlap in research. For instance, scientists Caesar Fragola and Elder de Turk list their disciplines as engineering and physics, respectively. Both work on aircraft instrumentation: Fragola examines “aircraft instrumentation engineering; development of aircraft flight and navigation instruments….” De Turk examines the “design and development of aircraft instruments; test of gravity meters; test, development and evaluation of aircraft armament systems.” Using *k*-means captures this overlap and assigns both scientists to the field of “aircraft.”

Giuliana Tesoro in the example above lists “organic chemistry” as her discipline and describes her research as “Synthesis of pharmaceuticals, textile chemicals, germicides and insecticides; synthesis and rearrangement of glycols in the hydrogenated naphthalene series.” While chemistry is too broad to be informative, the additional information on Tesoro’s research allows us to refine the field matching. Research topics and disciplines are known for 96.4% and 100% respectively of all 82,094 scientists in the MoS (1956).

### *2.2. Matching Scientists with Patents*

To measure variation in inventive productivity, we match scientists with patented inventions. Using information on the age, full name, and discipline of each scientist, we can establish a high-quality match between scientists and their patents. Starting from a standard Levenshtein (1966) distance measure, we use information on the scientist's age in the year of the patent application to filter out false positives, implementing a procedure from Moser and San (2021).

This improved matching process reduces the rate of false positive matches from more than 80% for the most naïve Levenshtein matching (ignoring middle names, disciplines, and name frequencies) to just 4.2% for the physical sciences. In the biological and social sciences, rates of false positives remain high, at 32.8% and 67.9%, respectively. To reflect such differences in data quality, we focus analyses of patents on the physical sciences and use data for other disciplines in supplementary analyses (which we also check with publications).

Patent data include 130,902 successful applications for US patents between 1930 and 1970 by American scientists. 35,368 STEM scientists created 122,935 patents. The median and average patent in our data has just 1 and 1.24 MoS inventors, respectively (with a standard deviation of 0.51). In the main specifications, field fixed effects control for variation in team size across fields. Robustness checks divide each patent by the total number of MoS inventors.

### *2.3. Matching Scientists with Publications*

To match scientists with publications we search for each scientist's name in the list of authors in Microsoft Academic Graph (MAG).[6] MAG is updated each week; we use the version from August 20, 2020. To perform the matching, we first restrict the data to English-language publications and to authors with at least one English-language publication between 1900 and 1960. We then match scientists in the MoS (1956) with a specific *authorid* in the MAG, using their first and last name, as well as their middle initial. For scientists who are matched with more than one author, we manually check and remove duplicates.

Our data include 754,581 journal publications by 70,189 scientists between the ages of 18 and 65 (10.8 per scientist) and 790,180 publications by 70,230 scientists between the ages of 18 and 80 (11.3 per scientist). 66.2% of 70,230 US scientists in the MoS (1956) have at least one publication. With 864 articles and books, Carl Djerassi, the inventor of oral contraceptives, has the largest number of publications. The embryologist Jane Marion Oppenheimer is the most published female scientist, with 240 publications.

The average publication has 2.27 authors (with a median of 2 and standard deviation of 2.25). To control for variation in the size of author teams, we divide publications by the number

[6] Moser and Parsa (2020) use publications to examine the effects of political persecution during the McCarthy era.

of authors in the main specifications; in robustness checks we count each publication once per author. Adjusting for the number of authors per paper, our data include the equivalent of 469,380.2 single-authored publications by 70,189 scientists between 18 and 65 (6.7 per scientist) and 493,249.7 single-author-equivalent publications by 70,230 scientists between 18 and 80 (7.0 per scientist). Field fixed effects control for variation in the size of author teams across fields.

We use citations to control for the quality of publications. These data include 141,952,592 citations to 754,581 publications by 70,189 scientists between 18 and 65 (188.1 per publication). The most highly cited paper is a 1951 article in the *Journal of Biological Chemistry* by Oliver Howe Lowery on "Protein measurement with the folin phenol reagent" (250,657 citations). The most highly cited paper by a female scientist is a 1962 paper by the cellular biologist Marilyn Gist Farquhar on "Junctional complexes in various epithelia" (5,156 citations), describing Farquahar's joint research with George E. Palade (Nobel 1974).

### *2.4. Matching Scientists with the Census*

To investigate whether access to childcare can mitigate the adverse career effects of children, we match 2,446 faculty members at Columbia University in 1943-45 (including 378 scientists who are in the MoS 1956) with individual records in the US Census. Using scientists' names, birth and graduation years, occupations, and locations we match 539 faculty members (22%) with their census records in 1940. Matched scientists include 466 men and 73 women; among them, 121 men and 10 women are in the MoS (1956).

For these 539 matched scientists, we use the census variable *incwage* to calculate household income by adding the income and wages earned by the scientist, their spouse, and other family members. Next, we use the variable *relstr* to identify scientists who had live-in help from grandparents or from people living in the same household who listed their occupations as servant, maid, cook, butler, houseworker, governess, tutor, teacher, chambermaid, or caretaker. We calculate the scientist's expenditure on live-in household help by adding values for *incwage* for people working in these occupations living in the scientist's household.

## III. Patented Inventions

In this section, we use successful patent applications to examine how children affect the inventive output of mothers, fathers, other women, and other men. First, we examine changes in productivity across the life cycle separately within demographic groups. Second, we document differences in patenting across demographic groups. Third, we estimate event studies of changes in patenting after marriage to investigate the causal effects of children on productivity.

### *3.1. Changes in Inventive Output across the Life Cycle*

A visual inspection of the patent data already reveals a unique life cycle pattern of productivity for mothers: While other demographic groups peak in their mid-30s, mothers become more productive after age 35 and reach peak productivity in their mid-40s (Figure 1, Panels A and B). Mothers create 31.8 patents per 1,000 scientists and year between the age of 45 and 49, roughly twice what they produce at age 27, the median age at marriage.[7] Scientists in all other demographic groups peak around their mid-30s. Fathers, for example, patent most at age 36 (185.3 patents per 1,000 scientists and year, Figure 1, Panel A).

To investigate these changes in productivity more systematically we estimate changes in patenting across the life cycle *separately within demographic groups*:

$$y_{iat}^{d} = \beta_a^d Age_i + \delta_t + \mu_f + \epsilon_{iat} \quad (1)$$

where inventive output $y_{iat}^{d}$ counts US patents, multiplied by 1,000, by scientist $i$ of demographic $d$ at age $a$ in calendar year $t$ of the patent application. The coefficient $\beta_a^d$ is a vector of age-varying estimates of productivity at age $a$ by scientists of demographic $d$ compared with scientists in the same demographic at age 20, the excluded age. $\delta_t$ are patent application year fixed effects to capture variation in patenting over time (e.g., as a result of variation in research funding); $\mu_f$ are field fixed effects that control for variation in the propensity to patent across fields $f$ (e.g., if scientists patent less in theoretical fields, like mathematical analysis, compared with applied fields, like chemical engineering, or if there is variation in patenting across industries, as in Moser 2012).

Age-specific estimates confirm the striking life-cycle pattern of productivity for mothers (Figure 2). Inventions by mothers increase until age 27 (the median age of marriage), slow until their mid-30s, and experience a boost in their forties, long after other scientists have started to decline. Compared with themselves at age 20, mothers produce just 45.5 additional patents per

[7] The rapid decline in inventive output after age 49 may be due to women leaving the work force. For cohorts before the 1950s, female labor force participation rose sharply between their 20s to late 40s but then declined when women reached their early 50s (Goldin and Mitchell 2017, p. 161). Mothers may be especially affected by declining labor force participation after age 50 if they took care of grandchildren.

1,000 scientists at age 32 (p=0.035) and 36.3 at age 34 (p=0.047). After age 35, their inventive productivity recovers, reaching 70.4 additional patents at age 42 (p=0.260).

Only mothers experience this late-in-life boost in productivity. Estimates of $\beta_a^f$ for fathers indicate that their productivity plateaus between 208.8 additional patents at age 35 (p=0.000) and 214.9 at age 40 (p=0.000). After 40, fathers' productivity decelerates to 177.1 additional patents at 45 (p=0.000), and 160.8 at 50 (p=0.000). Estimates of $\beta_a^{om}$ for other men show a similar pattern, with a peak at 163.3 additional patents at 38 (p=0.000) followed by a steady and persistent decline. The productivity of other women peaks at 30, and then declines to 19.7 additional patents at 35 (p=0.041), 20.9 at 40 (p=0.043), and 23.0 at 45 (p=0.053).

Examining US Census data, Goldin (2014) observes that the ratio of female to male earnings declines when people are in their twenties and thirties, but then increases when people reach their forties. Our findings suggest that this puzzling change in the gender earnings gap may be due to a differential late-in-life productivity increase for mothers, at least for science.

### *3.2. Differences in Inventive Output Across Demographic Groups*

Next, we examine differences across demographic groups to connect our results with existing research (e.g., Blau and Khan 1997, Bertrand, Goldin, and Katz 2010, and Jensen et al 2018). Examining patents, Bell et al. (2019) show that just 18% of inventors born in 1980 were women, up from 7% in 1940. We extend this analysis to earlier cohorts of inventors and scientists who were born between 1870 and 1930. Extending the slow progress towards gender parity in modern data, just 0.91% of scientist-inventors in these older cohorts were women.

To examine differences in inventive output across demographic groups more systematically, we estimate OLS models:

$$y_{it} = \beta_1 Parent_i + \beta_2 Female_i + \beta_3 Female_i * Parent_i + \delta_t + \pi_b + \mu_f + \epsilon_{it} \quad (2)$$

where the dependent variable $y_{it}$ counts US patents, multiplied by 1,000, by scientist $i$ in year *t*. The variable $Parent_i$ indicates scientists who were parents in 1956, $Female_i$ indicates scientists who are women, and $Female_i * Parent_i$ indicates scientists who are mothers; birth year fixed effects $\pi_b$ control for variation in scientific output across birth cohorts, e.g., as a result of differences in exposure to World War II. All other variables are defined as above, in equation (1).

OLS estimates confirm that mothers patent more than other women but much less than fathers and other men. On average, female scientists produced 67% fewer patents compared with men (with an estimate of 58.7 fewer patents per 1,000 scientists and year, Table 1, column 1, significant at 1%) compared with a pre-baby boom mean of 88.1 patents per 1,000 scientists and year. Mothers patented 77% less than fathers (-58.7-9.1 in Table 1, column 1 divided by the mean), but 9% more than other women (17.7-9.1 relative to the mean). All results are robust to controlling for age fixed effects (column 2, replacing cohort fixed effects), and to including older scientists up to age 80 (column 3). Estimates are also robust to controlling for the number of MoS scientists that are listed on each patent (Appendix Table A3).

We also find that fathers produce more patents than other men, with 17.0 additional patents per 1,000 scientists and year (Table 1, column 1, significant at 1%). These results are consistent with findings of higher earnings for fathers and other married men. Examining wages in manufacturing, Goldin (1990, pp. 91 and 102) documents that married men have earned around 17% more compared with single men since the 1890s, while there was no difference for married and single women. Analyzing the earnings of MBAs, (Bertrand et al. 2010, pp.248-9) find that, while earnings of female MBAs decline sharply three to four years after the birth of their first child, earnings by male MBAs increase for five years or more.

Higher patenting rates for fathers may reflect either selection or specialization; intensity estimates for the number of children suggest specialization. While the productivity of mothers is hit hardest by the first child, fathers became more productive with each child (Appendix Table A1). For the late 20th century, Korenman and Neumark (1987) show that the marriage premium increases with the duration of marriage as men with dependents increase their labor market efforts. In our setting, additional children may encourage men to produce more patents, which, as Kline et al. (2019) document, increase the earnings of men.[8]

Extending the analysis to the biological and social sciences suggests that gender differences in output are less pronounced in other disciplines compared with STEM. Relative to the pre-baby boom mean of 46.1 patents per year, an estimate of -24.3 for *Female* indicates that women patent "just" 52% less (Table 1, column 4). Yet, the effects of children are nearly identical in STEM and in analyses across all fields. Across all fields, mothers patent 71% less compared with fathers and 7% more than women without children. Arguably, patents are a noisy

[8] While we cannot examine same-sex families, Martell and Nash (2020) find that marriage encourages specialization similarly in same-sex and different-sex families. Using data on married gays and lesbians from the American Community Survey for 2013-17, they show that the marriage premium is double for the higher-earning spouse.

output measure for the biological and social sciences because important breakthroughs in both disciplines cannot be patented. We address this issue by repeating analyses for the biological and social sciences with publications.

### *3.3. Event Studies of Changes in Inventive Output after Marriage*

An ideal experiment to identify the causal effects of children would randomly assign children to scientists. Since this is impossible, we exploit the sharp change in productivity created by the birth of a child to estimate event studies for changes in patenting after marriage. While a scientist's choice to marry and have children may not have been exogenous, the event of marriage and the arrival of a child leads to a sharp change in productivity that is arguably orthogonal to unobserved determinants of productivity that evolve more smoothly over time. For example, one may believe that women who chose to have children are less serious about research. Changes in productivity that stem from these underlying preferences would evolve smoothly over time, while changes due to children happen more abruptly. Moreover, the event study approach allows us to investigate changes in productivity across a scientists' entire career. This feature is particularly important for capturing the effects of children on women whose productivity might be delayed.

Event study models estimate OLS equations

$$y_{ist}^{d} = \beta_s^d EventTime_i + \delta_t + \alpha_a + \mu_f + \epsilon_{ist} \quad (3)$$

where we index the event time *s* relative to the year of marriage, and $y_{ist}^{d}$ is the number of US, multiplied by 1,000, of scientist $i$ of demographic *d* (mothers, fathers, and other married women and men) in event year *s* and calendar year *t*. The coefficient $\beta_s^d$ is a vector of time-varying estimates of output in event year *s* by scientists of demographic *d* compared with scientists in the same demographic one year before marriage (the excluded year). Omitting the event time dummy at *s = -1* implies that event time coefficients $\beta_s^d$ estimate the impact of children relative to the last year before marriage. Age fixed effects $\alpha_a$ control for variation in output across the life cycle of scientists. Calendar year dummies and other variables are defined as above.[9]

[9] Since there is variation in event time *y* driven by the year of marriage (conditional on age and year) these specifications identify the effects of three separate time dummies for the calendar year *t*, the scientist's age *a* in year *t*, and event time *s*.

OLS estimates show a flattening of output for mothers after marriage, followed by a strong and sustained recovery after 15 years of marriage (Figure 3). After 25 years of marriage, mothers create 62.4 additional patented inventions (p=0.058) compared with themselves before marriage. Mothers continue to produce many patents, with 50.2 additional at 30 years after marriage (p=0.011).

This strong and sustained increase in productivity is unique to mothers. The inventive output of fathers peaks after 9 years of marriage, with 56.3 additional patents (p=0.000) and then declines steadily to 35.0 additional patents after 15 years (p=0.000), 11.0 additional patents after 20 years (p=0.154), and 5.2 fewer patents after 30 years (p=0.531). Event-study estimates for other men ($\beta_y^{om}$) follow a similar pattern, increasing to 53.4 additional patents after 9 years (p=0.006) and declining afterwards. Estimates for other women ($\beta_y^{ow}$) are similar to those for mothers for the first 15 years, but then decline like the estimates for men.

Why do mothers become more productive after 15 years of marriage? One hypothesis is that mothers accumulate research ideas while taking care of children. This hypothesis is at odds with fundamental results of high returns to experience in the labor market (e.g., Jacobson, Lalonde, and Sullivan 1993). Career disruptions damage future wages and job security, especially if they happen early in a person's career (e.g., Oreopoulus, von Wachter, and Heisz 2012, and Jarosch 2015). Examining the effects of incentivizing mothers to work after childbirth, Kuka and Shenhav (2020) show that mothers who faced increased incentives to return to work after the 1993 reform of the Earned Income Tax Credit accrued 0.5-0.6 additional years of work experience and had 4.2% higher earnings. In addition, women who leave jobs in science to raise children face skill depreciation, which is particularly salient in fast-moving fields. McDowell (1982) documents exceptional decay rates of knowledge for physics and chemistry. A "has-been" model of skill obsolescence shows that obsolescence increases with the pace of technological change (MacDonald and Weisbach 2004), which is especially high in science.

A simpler, more plausible explanation for the delayed productivity of mothers is that older children require less work and that the work associated with smaller children falls disproportionately on women. In 2019, mothers spent 2.8 hours per day caring for children under the age of 6, compared with 1.2 hours for children between 6 and 12 years old (US Bureau of Labor Statistics 2020). Fathers spent about half that time, with 1.4 and 0.7 hours per day, respectively. After 15 years of marriage, children who were born within the first five years were at least 10 years old.

In short, patent data indicate that children lead to a temporary reduction in the productivity of mothers, but not of fathers. Mothers experience an unparalleled increase in patenting late in life (after age 35) and late in marriage (after 15 years of marriage), long after the productivity of other scientists declines. The next section examines whether these patterns hold for publications and investigates implications for tenure and participation.

## IV. Publications and Tenure in Academic Science

Being more productive later in life may disadvantage mothers in decisions on promotions and tenure, which use early productivity as a predictor for lifetime achievements. In this section, we investigate this issue using data on publications and tenure.

### *4.1. Changes in Publications Across the Life Cycle of Scientists*

Publication data confirm the unique life cycle pattern of productivity for mothers (Figure 4). Publications by mothers increase up to the median age at marriage (27), reaching 9.1 publications per 100 scientists and year, and stay flat afterwards (Panels A and B). In their late 30s, mothers experience a productivity boost that is even more sustained than the increase for patents. Mothers publish many papers in their 40s (16.3 publications per 100 scientists and year) and 50s (16.6 publications). By comparison, publications by fathers peak in their late 30s (slightly later than patents with 28.0 publications per 100 scientists and year between 35 and 39, Panels A and D).

Age-specific estimates of equation (1) corroborate the strong and sustained productivity increase for mothers in their 40s and 50s (Figure 5). Until age 27, publications by mothers and fathers follow a similar trend. After the age of 27, publications by mothers plateau, while those by men continue to increase. At ages 31 and 37 mothers publish 13.9 and 11.4 additional papers per year, respectively, compared with themselves at age 20 (p=0.000 for both). After age 37, mothers begin to publish more, reaching 18.1 and 18.9 additional publications at ages 42 and 48, respectively (p=0.000 for both). By comparison, the productivity of fathers peaks with 22.7 additional publications at 38, declines to 21.1 at 45, 18.3 at 50, and 15.5 at 55 (p=0.000 for all).

### *4.2. Differences in Publishing Across Demographic Groups*

Comparisons of publications across demographic groups cross-validate our findings based on patents. OLS estimates of equation (2) for publications imply that women in STEM publish 64% less than men (with an estimate of -6.942 for *Female* in Table 2, column 1, significant at 1%, relative to a pre-baby boom mean of 10.8 publications per 100 scientists and year). Mothers publish 75% less than fathers (-6.942 for *Female* and -1.155 for *Female*Parent* in Table 2, column 1), and roughly the same as other women (0.665 for *Parent* and -1.155 for *Female*Parent*). All results are robust to controlling for age fixed effects (columns 2 and 5) and to including older scientists (columns 3 and 6). Citation data indicate that women are cited less (with an estimate of -1.731 for *Female*, significant at the 1% level, Table 2, column 8), consistent with evidence on gender differences in credit for research (Sarsons et al. 2021).

Confirming results from patents, gender differences are less pronounced in the biological and social sciences, and the effects of parenting are similar. Across all disciplines, female scientists publish 59% less than men (with an estimate of -8.110 for *Female* Table 2, column 4 compared with a pre-baby boom mean of 13.9 publications per 100 scientists and year). Results for parenting, however, are nearly identical for STEM and other scientific disciplines. Mothers publish 66% less than fathers (with an estimate of -8.811 for *Female* and -1.021 for *Female*Parent* in Table 2, column 4), and slightly more than other women. Mothers also publish slightly more across all disciplines (-1.021 for *Female*Parent* and 0.233 for *Parent*).

Why do mothers *publish* roughly the same amount as other women, while they *patent* slightly (8%) more? These differences could reflect differences in the intensity of selection or in productivity. Bertrand, Goldin, and Katz (2010) as well as Goldin (2014) document gender differences in time flexibility. Applying this idea to the context of scientific production, mothers may find it harder to accommodate the inflexible time demands of laboratory work, so that only the most productive mothers survive and patent in STEM. Alternatively, motherhood may reduce the publishing productivity of mothers in academia more than in science, if mothers are less likely to get tenure. We examine both channels below.

### *4.3. Mothers (but not Other Women) Are Less Likely to Get Tenure*

Previous research has shown that female scientists are promoted more slowly than men (e.g., National Academy of Sciences 2006); we find that gender differences in the rate and speed of promotions are driven primarily by mothers (Table 3). Among academic scientists, just 27% of mothers achieved tenure compared with 48% of fathers. At 46%, tenure rates for women without children are nearly identical to rates for men. While mothers are heavily penalized for parenting, fathers are slightly more likely to get tenure than other men. 48% of fathers get tenure, compared with 47% of other men.

These findings suggest that, when mothers have carried a disproportionate share of childbearing and child-rearing responsibilities, gender-neutral tenure policies for parents have held back female scientists. Evidence from economics suggests that these patterns persist today. Examining tenure rates for assistant professor hires at top-50 economics departments between 1980 and 2005, Antecol, Bedard, and Sterns (2018) show that gender-neutral tenure clock stopping policies have substantially reduced tenure rates for women while increasing tenure rates for men.

### *4.4. Mothers Face Higher Standards of Early Productivity*

Comparisons of tenure rates over time reveal a striking divergence between mothers and other scientists six years after starting a tenure-track job (Figure 6). Counting from their first year as an assistant professor, mothers have comparable tenure rates initially, reaching 30% in year 6. After year 6, however, tenure rates for mothers plateau below 40% while tenure rates for fathers continue to increase. 15 years after starting as an assistant professor, 62% of fathers have tenure. Notably, other married women initially fall behind along with mothers but close some of the gap with unmarried women and men in later years, as their risk of motherhood declines.[10] These differences suggest that mothers may be held to a higher standard of early productivity.

Mothers who are academic scientists are also much less likely to get tenure-track jobs compared with other scientists. Typically, mothers who are academic scientists stay off the tenure track, mostly as instructors. Just 35.9% of mothers get appointments as tenure-track assistant professors compared with 44.6% of other women and 45.4% of fathers (Table 3). Mothers also

[10] Another possible force reducing tenure rates for women is the plight of the “trailing spouse.” Topel and Ward (1992) find that the average male worker switches jobs seven times in their first ten years in the labor market, and that these job changes account for at least a third of early-career wage growth. While such job mobility benefits scientists, it hurts wives who must move along. Using US and UK census microdata to identify couples who move together, Boyle et al. (2001) show that women’s employment is harmed by family migration. Examining linked employer-employee data for the Great Recession, Lachowska, Mas, and Woodbury (2020) find that the loss of worker-employer matches explains more than one-half of lost earnings for displaced workers.

wait three times as long as fathers to get their first tenure-track job (4.4 years after their PhD) compared with fathers (1.3 years) and women without children (2.8 years, Appendix Figure A5).

*4.5. Publishing Across the Life Cycle - Scientists with and without Tenure*

To examine the link between publications and tenure we re-estimate age-varying effects in equation (1) separately for scientists with and without tenure (Appendix Figure A4). These estimates show that mothers publish more in their 40s and 50s, irrespective of tenure, while other scientists slow down after their mid-30s (Appendix Figure A4). By 42, mothers with tenure publish 27.5 (p=0.000) additional papers compared with themselves at age 20 (Panel A). By 57, they publish 28.0 additional papers, compared with just 18.2 and 13.8 additional papers by fathers and other women, respectively (p=0.000 for all).

Even mothers who do not attain tenure are exceptionally productive in their 40s and 50s. At age 58, mothers without tenure publish 21.9 additional papers, roughly twice as many compared with 11.5 for fathers and just 8.9 for women without children (p=0.000 for all).

Compared with mothers who get tenure, mothers who do not get tenure show a larger decline in output in their 30s (Panel B). At age 35 and 40, mothers who ultimately do not get tenure publish just 12.1 and 11.5 additional papers, respectively (p=0.000 for both). These differences indicate that productivity differences in their 30s are critical for tenure rates of mothers, even though they may be a poor predictor of future productivity.

*4.6. Event Study Estimates of the Effects of Children on Tenure*

To investigate the causal effects of children on a scientist's probability of tenure, we estimate event studies analogous to equation (3) for tenure:

$$y_{ist}^{d} = \beta_{y}^{d} EventTime_{i} + \delta_{t} + \mu_{f} + \epsilon_{ist} \quad (4)$$

where the event time *s* is indexed relative to the year of marriage. Now $y_{ist}^{d}$ is the probability that scientist $i$ in demographic *d* holds a tenured job in event year *s* and calendar year *t*. The coefficient $\beta_{s}^{d}$ is a vector of time-varying estimates for the probability of holding a tenured job after *y* years of marriage for a scientist of demographic *d* relative to the probability of promotion to tenure in the year before marriage. All other variables are as defined in equation (3).

Estimates of $\beta_{y}^{m}$ for mothers (Figure 7) confirm that children reduce tenure probabilities for women but not for fathers. After 15 and 20 years of marriage, mothers are only 16.0%

(p=0.000) and 25.5% (p=0.000) more likely to have tenure compared with themselves one year before marriage (Figure 7). By comparison, fathers are 58.7% more likely after 15 years (p=0.000), 72.3% after 20 years (p=0.000), and 94.4% after 30 years (p=0.000). Event-study estimates for other married men ($\beta_y^{om}$) follow a similar pattern over time, although at lower levels. Married women without children occupy a middle ground between men and mothers: after 15 years of marriage, they are 31.8% (p=0.000) more likely to have tenure. Estimates increase to 41.7% after 20 years (p=0.000), 48.4% after 25 years (p=0.000), and 60.0% after 30 years (p=0.000).

### *4.7. Mothers Publish More after Tenure, while Other Scientists Plateau*

To examine changes in productivity before and after tenure, we re-estimate event studies in equation (3) relative to tenure. While these estimates cannot measure a causal effect of tenure on publications (because ideally, tenure is a result of publications), event study estimates allow us to compare changes in productivity for scientists in different demographic groups.

Event study estimates show that mothers become more productive after tenure, reaching peak productivity 5 to 10 years after tenure (Figure 8). By comparison, the output of other scientists either stays flat or declines after tenure. Male scientists with and without children publish more leading up to tenure; after tenure, their productivity stays flat. Other women see a decline in productivity after tenure. Only mothers become more productive after tenure.

## V. SELECTION

Compared with other scientists, mothers are more productive later in life and after 15 years of marriage. In this section we explore whether these patterns may be due to selection which allows only the most productive mothers to survive in science. Specifically, we examine selection into motherhood, PhD education, research fields, and survival in academic science.

### *5.1. Mothers are Extremely Positively Selected*

Most importantly, we find that mothers who survive in science are extremely positively selected. Leading up to the median age of marriage at 27, mothers patent 5.3 and 2.5 times as much as single women and childless married women, respectively (Table 4). These results are particularly striking given that we may underestimate the productivity of married women before marriage:

since many women in these cohorts changed their name upon marriage, married women are harder to match with their pre-marriage papers compared with men and other women.

Mothers also publish 1.3 times more than single women and other married women each, and their papers are more highly cited (Table 4). Papers that mothers publish before age 27 receive 18.3 citations per paper, compared with 11.7 by single women and 7.8 by other married women.

Fathers, by comparison, are less positively selected, especially in terms of publications. Fathers patent more than other married men (34.4% more) and single men (17.9% more), but they publish 4.1% less than other married men and 11.3% more than single men, and their papers are less cited (Table 4). Since patents increase earnings (and men are more likely to benefit from patents issued to their firm, Kline et al. 2019), these results suggest that fathers may be positively selected for their earnings potential but not for publications.

### *5.2. Women are More Likely to Have PhDs*

Models of human capital investment imply that women, who spend less time in the labor market, have weaker incentives to invest in human capital that is valued by the labor market, such as a PhD (e.g., Altonji and Blank 1999, p. 3166-67). Women also face formal and informal barriers in access to education, which may discourage them from pursuing a PhD. In the 1950s and 60s, many graduate departments still refused to admit female applicants (Kevles 1995, p.371), and even departments that admitted women struggled to support them. Seeking an advisor at Harvard in the 1960s, the future “Queen of RNA” Joan Steitz was turned down by a professor: “but you are a woman, and you’ll get married, and you’ll have kids, and what good will a PhD have done?” (Lucci-Cannapiri 2019).[11] Yet, if there is labor market discrimination, women may decide to invest in pursuing a PhD, despite these obstacles, because they must be more qualified to get the same jobs.

Consistent with the presence of labor market discrimination, women in the MoS were *more likely* to have PhDs. 84% of women had a PhD compared with 78% of men. Mothers were slightly less likely to hold a PhD than other women (83.2% compared with 84.4%), while fathers were the least likely to have a PhD (with 76.6% compared with 79.8% for other men).

[11] In the population, gender differences in education have narrowed since the baby boom; with the convergence of education, the gender wage gap has narrowed too (Blau and Khan 1997).

### *5.3. Female Scientists are Less Likely to Marry and Have Children*

Female scientists appear to have internalized the career costs of children by having fewer children, marrying less, and marrying later in life. For instance, female scientists were less than one-third as likely to have children compared with men. 22.1% of female scientists had children, compared with 74.0% of men. While it became more common for female scientists to have children over time, women remained less likely to have children across our sample period (Appendix Figure A6, Panel C). For female scientists, the share of mothers increased from 17.0% of those born before 1906 (and above 40 at the start of the baby boom) to 26.2% of women in born before 1916 (in their 30s) and 29.0% for women born 1916-25 (and in their 20s at the start of the baby boom). For men, the share of parents increased only slightly, from 71.5% to 74.8%.

Female scientists were also less than half as likely to marry compared with men. Just 38.8% of female scientists married, compared with 84.2% of men. Like the share of mothers, the share of married women increased over time, but it remained substantially below the share of married men. Among the oldest cohort of scientists (above 40 in 1945), only 29.7% of female scientists married, compared with 79.1% of male scientists. Among the cohort of baby boom parents, 51.0% of women married, compared with 87.7% of men (Appendix Figure A6, Panel A).

Female scientists also married less and were less likely to have children compared with other college-educated women. Examining notable American women, Goldin (2021, pp. 25-30) shows that less than 30% of women born between 1878 and 1897 had children and just over half ever married. College-educated women in this cohort chose between family and career. The next generation, born 1898-1923 first achieved a job and then a family. Only an exceptional few of them worked for pay after marriage. Among college-educated women born 1924-43, 90% married and 90% among them had children (Goldin 2021, p. 37); women in this cohort had a family and then a job.[12]

If female scientists married, they married late, much later than other college-educated women or even men.[13] The US Census (1960) estimated that the median US woman married at

[12] Bertrand et al. (forthcoming) find that the difference in marriage rates between college-educated and other women increased for women born from the early 1930s to the mid-50s but declined for younger cohorts. Since the 1960s, college-educated women have been more likely to marry than other women.

[13] Miller (2011) shows that each year of delaying marriage increases work hours by 6%, earnings by 9%, and wages by 3%, with larger increases for college-educated women. Low (2021), however, finds that delaying motherhood is costly if potential marriage partners value reproductive capital, which deteriorates over time. As a result, women with advanced degrees who delay marriage tend to marry partners who earn less.

age 20.9 years, while the median man married at the age of 22.8. College-educated women married significantly later, at a median age of 24.0 years in 1960, compared with 25.5 for men. Scientists married even later than the college-educated, at a median age of 27 (Appendix Figure A7). Moreover, female scientists married *later* than men on average (at 28.8 compared with 27.6 for men). Over time, scientists' age of marriage declined, but female scientists continued to marry much later than other college-educated women (Appendix Figure A7).

### *5.4. Selection into Fields*

Goldin (2014) documents strong correlations between job flexibility and the gender wage gap, which suggests that women may be willing to accept lower wages in return for flexible hours. By the same mechanism, female scientists may accept work in fields with lower productivity to avoid the inflexible schedule of laboratory work. In the main specifications, we control for this issue through field fixed effects. Here, we directly investigate selection into fields by comparing the productivity of fields with low and high shares of women.

Women overall appear to be slightly less likely to select into patent-intensive and slightly more likely to sort into publication-intensive fields, but there is no difference between mothers and other women. For mothers, the correlation between the share of scientists in a field and the number of patents per scientist in that field is small and negative (at -0.1697, Appendix Table A4); this correlation is almost identical for mothers and other women (-0.1688). For fathers and other men, the correlation is close to zero (with 0.0006 for fathers and -0.0464 for other men).

These findings are consistent with existing research on earnings, which suggests that selection into occupations accounts for only a small share of gender differences in earnings. Two-thirds (68%) of the gender-based difference in earnings across 469 occupations in the US census comes from factors *within* occupations (Goldin 2014, p.1098). Among German women who enroll in two- to three-year occupational training programs after high school around the age of 16, selection into child-friendly occupations accounts for only a small share of the total earnings loss from children (Adda, Dustman, and Stevens 2017).

Our research also challenges the view that selection and preferences are a root cause of the persistent underrepresentation of women in STEM. Articulating this view to explain the low share of women in American physics in the 1950s and 60s Kevles (1971, p. 371) argues that

> …professionally oriented women still aspired to the more 'womanly' professions. Classes in high-school chemistry, which could open the door to careers in such fields as home economics, nutrition, or nursing, enrolled almost as many girls as boys; in physics courses, boys outnumbered girls three to one.

Empirical support for this view is limited at best. Conditional on surviving in American science, women are *overrepresented* in physics, mathematical analysis, and other STEM fields. 3.7% of female scientists worked in physics, more than six times compared with just 0.6% of men (Appendix Figure A8). Another 5.0% of female scientists worked in mathematical analysis, more than twice the 2.0% of men.

The prominence of women in mathematical analysis and physics is especially striking given that women faced major barriers to entry in these fields. Their overrepresentation may reflect a high "price of prejudice" (Hedegaard and Tyran 2018; Becker 1957) in fields that depend on rare talents,[14] where discriminating employers assign women and minorities to lower status positions as *hidden figures* (Shetterly 2016) while still using their skills.

*5.5. Women were Half as Likely to Survive in Science Compared with Men*

To examine survival in science we digitized pre-baby boom faculty rosters of Columbia University for 1943-5 and combined them with existing rosters from the UC Cliometric History Project for Stanford, UCLA, and UC Berkeley for the same years.[15] We then used algorithmic and manual matching to identify faculty members who survived to enter the MoS (1956).

Linking faculty records with the MoS (1956), we find that women were half as likely to survive in science. Just 9.8% of female faculty in 1943-45 survived to enter the MoS in 1956, compared with 19.8% of men at the same universities. Moreover, the share of parents among surviving faculty is three times as high for fathers compared with mothers: 25.3% of surviving female scientists were mothers, compared with 73.6% of male scientists.

[14] Becker (1957) describes the costs of prejudice in a chapter on "price and prejudice." Experimental evidence in Hedegaard and Tyran (2018) shows that discriminators respond to the cost of prejudice in terms of lost wages when they choose less productive co-workers based on their preferences over ethnic grounds.

[15] Among 4,811 faculty members at Columbia, Stanford, UCLA, and UC Berkeley in 1943-45, 808 were women (16.8%) and 4,003 were men (83.2%). Faculty records for the California universities are from the UC Cliometric History Project, available at http://uccliometric.org/faculty/, accessed August 1, 2020.

*5.6. Missing Mothers of the Baby Boom*

So far, we have shown that children influence the timing of productivity and that gender differences in tenure rates are driven primarily by children. In this final section, we investigate whether children also influence participation. Changes in the number of scientists per birth year indicate a substantial decline in participation for the mothers of baby boom (Figure 9). For women who were born after 1915, who would have been in their 20s during the baby boom, participation declines in absolute and relative terms. The generation born in 1921 produced just 93 female scientists, down from 118 female scientists born in 1915. At the same time, the number of male scientists increased from 2,432 born in 1915 to 2,528 in 1921.

Comparing rates of participation across birth cohorts, we estimate that nearly 180 female scientists – the missing mothers of the baby boom – were lost to American science. Had the baby boom mothers participated in US science at the same rate as earlier cohorts, a counterfactual total of 1,100 female scientists born from 1916-1925 would have been active in science by 1956, 177 more compared with the 923 women who survived to enter the MoS (1956).[16]

*5.7. Were Women with Access to Child Care More Likely to Survive?*

Improved access to childcare is a promising policy tool to help mothers to remain in science. To examine whether access to childcare improved the odds of surviving in science, we match 2,446 scientists who worked at Columbia University immediately before the baby boom (in 1943-45) with their census records and the MoS (1956).[17] Census data include information on household income, the presence of live-in household help, and expenditures on household help, which we use to proxy variation in access to household help. 73 of 539 matched Columbia faculty were women (13.5%), and 6 of them were mothers (1.1%). 10 of the matched female faculty (just 14% of the 73 matched faculty) survived in science long enough to enter the MoS.

Notably, only 1 of the 10 women who survived in science, the dermatologist Dr. Beatrice Maher Kesten, was a mother. Born in 1899, Kesten married in 1925 and had two children. In the census of 1940, Kesten and her husband report a joint income of $6,400 in 1940, employed a

[16] For birth cohorts 1900-15, 110 women per birth year were scientists. For scientists in birth cohorts 1916-25, who would have been in their 20s at the beginning of the baby boom, just 92.3 women became scientists.

[17] Methodologically, we determine the scientist's location in 1940 using biographical data on their place of employment and education in that year and then use first, middle, and last names, along with work or university locations and age in 1940, to hand-match faculty with the census. Through this process, we match 539 of 2,446 Columbia faculty (22%), including 73 women (14%).

"servant," and paid their servant a total of $900 per year. By comparison, mothers who did not survive in science had a much lower income (with an average of $3,960), were less likely to have household help (just 1 in 5) and spent only $72 on such help.

By comparison, fathers who survived in science were no more likely to have household help than non-surviving fathers: 26 of the 65 surviving fathers (40%) lived in households with maids, servants, and tutors; this is the same percentage as other fathers who did not survive in science (75 in 190, or 39.5%).[18] Fathers who survived in science earned roughly the same as non-surviving fathers (with average incomes of $3,411 and $3,438, respectively), though they spent more on household help ($533 compared with $378).

While these analyses of census records are limited in power due to the small number of observations, our results suggest that the ability to pay for childcare and other household helped women to survive in science, highlighting the promise of childcare as a policy tool.

## VI. Conclusions

Linking rich biographical data on 83,000 American scientists with their patents and publications, we document a unique lifecycle productivity pattern for mothers: mothers' productivity flattens after the median age at marriage but recovers in their mid-30s, when their children have presumably become less work. While other scientists peak around the age of 35, the productivity of mothers increases and remains high through their 40s (for patents) and 50s (for publications). Event study estimates show that mothers experience a large increase in productivity after 15 years of marriage, when the time requirements of raising children become less intense.

Differences in the timing of productivity have important implications for tenure and participation: Just 27% of mothers who are academic scientists obtain a tenured job compared with 48% of fathers and 46% of women without children. Mothers get tenure at comparable rates during the first six years after becoming assistant professors but fall behind dramatically afterwards, suggesting that they may be held to higher standards of early productivity than other scientists. Mothers also publish more after tenure, while the productivity of other scientists increases up to the tenure year and then flattens afterwards. Taken together, these results suggest that tenure processes which prize early productivity are biased against mothers whose early productivity is a poor predictor of their lifetime achievements.

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[18] 121 of 466 male scientists survived to enter the MoS (30.0%) and 65 of them were fathers (53.7%).

During the baby boom, the significant burden of raising children fell almost entirely on mothers. Comparing rates of participation across birth cohorts, we estimate that roughly 180 female scientists – the missing mothers of the baby boom – were lost to American science. By eliminating a generation of female role models, this loss affects science to this day. Having a female professor increases the performance of female students in math and science, as well as their likelihood of taking more math and science and graduating in STEM (Carrell, Page, and West 2010), yet many female professors were lost to science during the baby boom. In addition, the loss of baby boom mothers may have delayed changes in preferences that are shaped by observing parents who work. Fernández, Fogli, and Olivetti (2004) find that a positive shock to female labor force participation, which increased exposure to working mothers, changed the preferences of both women and men.

Since the 1950s, women have caught up in many dimensions of education and employment. Women who were born in the 1950s narrowed the gender gap in college attendance and graduation, in the attainment of professional degrees, and in employment in nontraditionally female occupations (Goldin 2006). Recent estimates indicate that 20 to 25% of US growth since 1960 is due to reduced barriers to the education, training, and employment of women and minorities (Jones et al 2019). But many of the barriers faced by the women in our data continue to operate today. For example, a new World Bank database on the legal treatment of women documents large and persistent gender inequalities regarding pay and parenthood across 190 countries (Hyland, Djankov and Goldberg 2020). Combined with our research, these findings suggest that better policies to support mothers in science could create major welfare gains.

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TABLE 1 – DIFFERENCES IN INVENTIVE OUTPUT ACROSS DEMOGRAPHIC GROUPS

| | Patents per 1,000 scientists | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Female | -58.695*** | -56.272*** | -52.453*** | -24.323*** | -25.033*** | -21.886*** |
| | (1.731) | (1.743) | (1.560) | (0.674) | (0.672) | (0.609) |
| Parent | 17.720*** | 18.982*** | 16.750*** | 11.862*** | 10.978*** | 10.888*** |
| | (1.350) | (1.382) | (1.250) | (0.683) | (0.682) | (0.629) |
| Female*Parent | -9.116** | -10.897*** | -12.927*** | -8.475*** | -7.953** | -9.235*** |
| | (3.892) | (3.916) | (3.659) | (1.252) | (1.254) | (1.164) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Birth year FE | Yes | No | Yes | Yes | No | Yes |
| Age FE | No | Yes | No | No | Yes | No |
| Field FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Disciplines | STEM | STEM | STEM | All | All | All |
| Scientists' age | 18-65 | 18-65 | 18-80 | 18-65 | 18-65 | 18-80 |
| N (scientists x years) | 1,204,592 | 1,204,592 | 1,298,053 | 2,391,179 | 2,391,179 | 2,591,524 |
| Pre-baby boom mean | 88.107 | 88.107 | 87.524 | 46.063 | 46.063 | 45.792 |

*** denotes significance at the 1-percent level, ** at the 5-percent level, and * at the 10-percent level

*Notes:* OLS estimates of differences in the number of patents issued to 1,000 scientists in different demographic groups per year between 1930 and 1970. $Female_i$ is an indicator for women, $Parent_i$ indicates scientists who were parents in 1956, and $Female_i * Parent_i$ identifies mothers. Robust standard errors in parentheses. Columns (1)-(3) present estimates for the physical sciences (STEM). Columns (4)-(6) include scientists across all disciplines, covering STEM, the biological, and the social sciences.

TABLE 2 – DIFFERENCES IN PUBLICATIONS AND CITATIONS ACROSS DEMOGRAPHIC GROUPS

| | Publications per 100 scientists (1-6) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Female | -6.942*** | -7.372*** | -6.467*** | -8.110*** | -8.202*** | -7.349*** |
| | (0.280) | (0.277) | (0.254) | (0.181) | (0.179) | (0.166) |
| Parent | 0.665*** | -0.213* | 0.696*** | 0.233** | -0.215** | 0.289*** |
| | (0.133) | (0.130) | (0.124) | (0.104) | (0.104) | (0.097) |
| Female*Parent | -1.155** | -0.823 | -1.083** | -1.021*** | -0.971*** | -1.320*** |
| | (0.556) | (0.554) | (0.531) | (0.319) | (0.319) | (0.302) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Birth year FE | Yes | No | Yes | Yes | No | Yes |
| Age FE | No | Yes | No | No | Yes | No |
| Field FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Disciplines | STEM | STEM | STEM | All | All | All |
| Scientists' age | 18-65 | 18-65 | 18-80 | 18-65 | 18-65 | 18-80 |
| N (scientists x years) | 1,204,592 | 1,204,592 | 1,298,053 | 2,391,179 | 2,391,179 | 2,591,524 |
| Pre-baby boom mean | 10.813 | 10.813 | 10.779 | 13.860 | 13.860 | 13.826 |

*** denotes significance at the 1-percent level, ** at the 5-percent level, and * at the 10-percent level

*Notes:* OLS estimates of differences across demographic groups in the number of author-weighted publications issued to 100 scientists (columns 1-6) and author-weighted citations per scientist (columns 7-8) per year between 1930 and 1970. $Female_i$ is an indicator for women, $Parent_i$ indicates parents. Robust standard errors in parentheses. Columns (1-3) present estimates for the physical sciences (STEM). Columns (4)-(6) include estimates across all disciplines, covering STEM, the biological, and the social sciences.

TABLE 3 – THE PIPELINE OF MOTHERS IN ACADEMIC SCIENCE, COMPARED WITH OTHER SCIENTISTS

| | Mothers | Women without children | | | Fathers | Men without children | | |
|---|---|---|---|---|---|---|---|---|
| | | All | Married | Single | | All | Married | Single |
| Academic scientists / all scientists | 84.5% | 88.6% | 86.7% | 89.2% | 73.8% | 77.1% | 74.1% | 80.4% |
| Tenure track / academic scientists | 35.9% | 44.6% | 38.2% | 46.4% | 45.4% | 45.9% | 45.7% | 46.1% |
| Tenured / academic scientists | 26.8% | 45.7% | 29.2% | 50.6% | 47.8% | 47.2% | 41.8% | 52.6% |
| N academic scientists | 754 | 2,783 | 636 | 2,147 | 36,140 | 13,269 | 6,616 | 6,653 |

*Notes: Academic scientists / all scientists* reports scientists who held university appointments as a share of all scientists. *Tenure track / academic scientists* presents the share of scientists with tenure-track jobs among academic scientists. *Tenured / academic scientists* measures the share of tenured professors among academic scientists. Data include 70,230 MoS (1956) scientists across all disciplines.

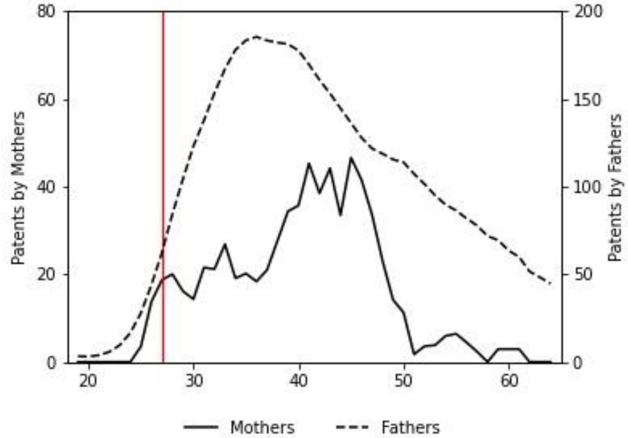
TABLE 4 – SELECTION INTO PARENTING: PRODUCTIVITY DIFFERENCES BEFORE THE MEDIAN AGE AT MARRIAGE

| | Mothers | Women without children | | | Fathers | Men without children | | |
|---|---|---|---|---|---|---|---|---|
| | | All | Married | Single | | All | Married | Single |
| Patents | 31.75 | 7.61 | 13.22 | 5.77 | 124.98 | 98.84 | 93.19 | 106.13 |
| | (503.95) | (98.67) | (148.15) | (75.81) | (984.95) | (805.14) | (738.12) | (884.09) |
| Publications | 25.16 | 19.65 | 18.83 | 19.89 | 37.68 | 36.56 | 39.28 | 33.86 |
| | (87.07) | (73.95) | (68.56) | (75.48) | (123.36) | (133.91) | (126.16) | (141.16) |
| Citations | 18.25 | 10.81 | 7.97 | 11.73 | 11.10 | 11.49 | 11.50 | 11.48 |
| | (84.43) | (36.90) | (12.66) | (41.83) | (51.70) | (32.60) | (32.66) | (32.53) |
| N STEM | 252 | 920 | 227 | 693 | 25,829 | 8,367 | 4,711 | 3,656 |
| N academic | 754 | 2,783 | 636 | 2,147 | 36,140 | 13,269 | 6,616 | 6,653 |

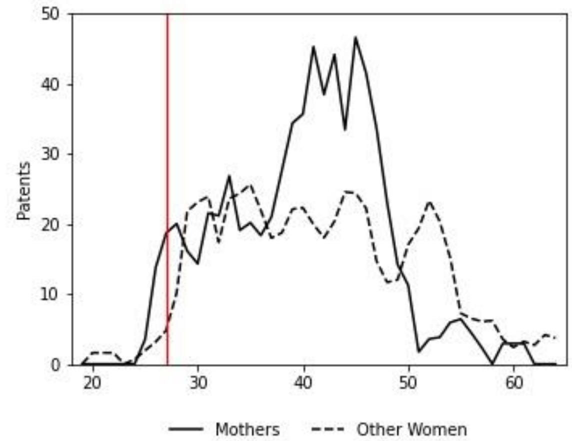
*Notes:* To investigate selection, we examine differences in scientific output up to the median age of marriage, which is 27 for both male and female scientists in the MoS (1956). Patents are reported per 1,000 scientists, publications per 100 scientists, and citations per publication. Data cover 4,070 patents issued to 35,368 STEM scientists, and 19,205 author-weighted publications (379,251 author-weighted citations) between 1930 and 1970 and between the ages of 18 and 27 by 52,946 academic scientists.

FIGURE 1 – LIFE CYCLE PRODUCTIVITY, PATENTS IN STEM

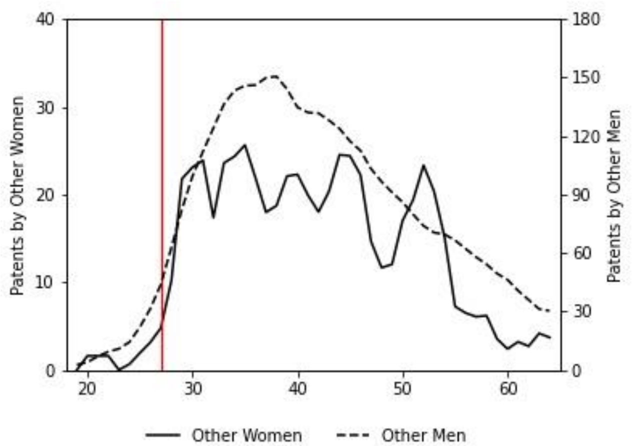
PANEL A: MOTHERS VS FATHERS



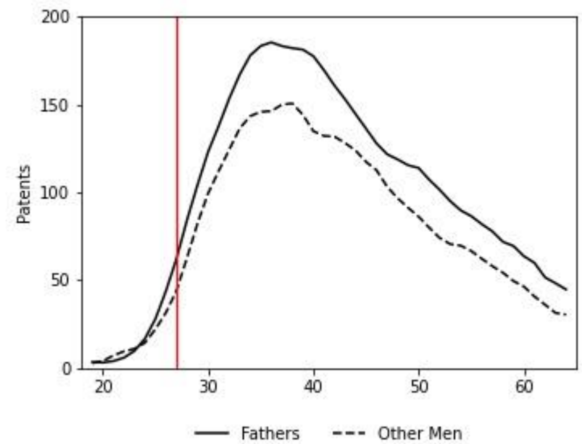

PANEL B: MOTHERS VS OTHER WOMEN




PANEL C: MEN VS WOMEN W/O CHILDREN

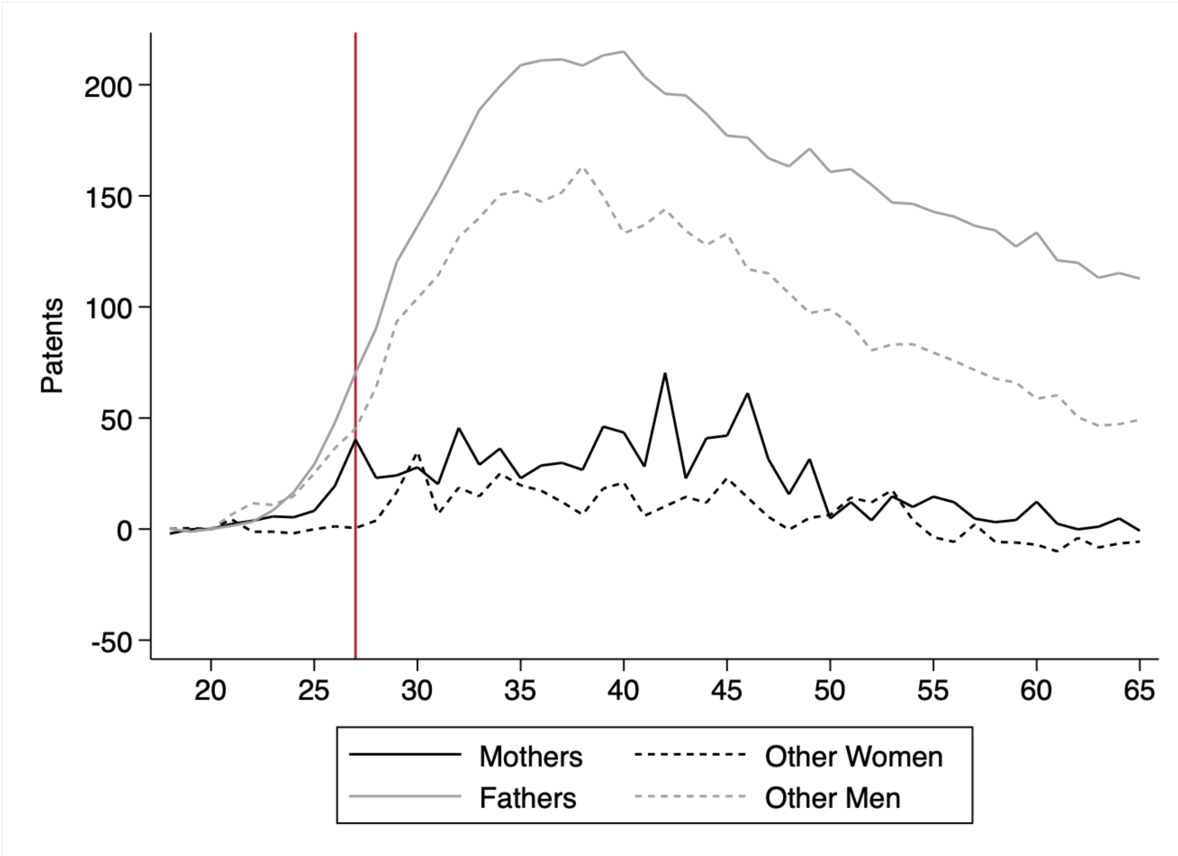



PANEL D: FATHERS VS OTHER MEN




*Notes:* Changes in productivity across the life cycle, measured by a three-year moving average of patents per 1,000 STEM scientists and year. The vertical line marks the median age of marriage for both female and male scientists, which is 27 years. Data include 121,321 successful applications for US patents issued between 1930 and 1970 to 35,368 STEM scientists.

FIGURE 2 – AGE-VARYING ESTIMATES OF LIFE-CYCLE PRODUCTIVITY IN STEM



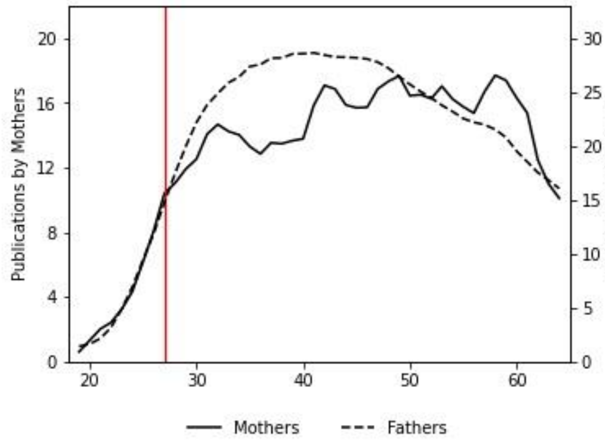

*Notes:* OLS estimates of $\beta_a^d$ for demographic $d$ (mothers, fathers, other women, and other men) in the equation $y_{iat}^d = \beta_a^d Age_i + \delta_t + \mu_f + \epsilon_{iat}$ where $y_{iat}^d$ are patents per 1,000 STEM scientists of demographic $d$ in age $a$ and calendar year $t$. The vertical line at age 27 marks the median age of marriage for both female and male scientists. The coefficient $\beta_a^d$ is a vector of age-varying estimates of inventions created by scientists of age $a$ and demographic $d$ compared with scientists in the same demographic at age 20. Calendar year fixed effects $\delta_t$ control for variation in patenting over time; field fixed effects $\mu_f$ control for variation in patenting across fields $f$. Data include 121,321 US patents by 35,368 STEM scientists.

FIGURE 3 – EVENT STUDIES OF CHANGES IN INVENTIVE OUTPUT AFTER MARRIAGE

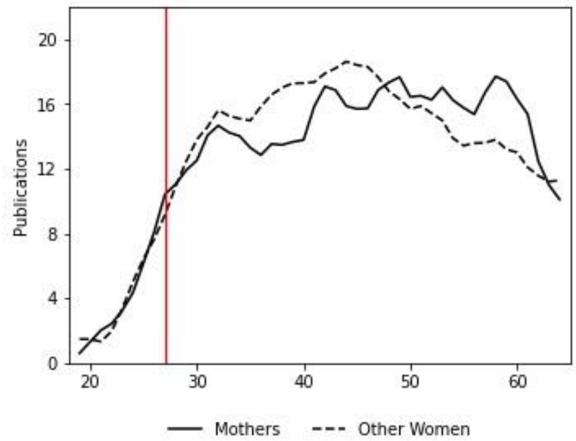

*Notes:* OLS estimates of $\beta_s^d$ for demographic $d$ (mothers, fathers, other married women, and other married men) in the equation $y_{ist}^d = \beta_s^d EventTime_i + \delta_t + \alpha_a + \mu_f + \epsilon_{ist}$ where $y_{ist}^d$ counts successful patent applications per 1,000 STEM scientists of demographic $d$ and year $s$ relative to the year of marriage and calendar year $t$. The coefficient $\beta_s^d$ is a vector of time-varying estimates of inventions in year $s$ relative to the year of marriage by scientists of demographic $d$ compared with scientists in the same demographic one year before marriage. $\delta_t$ are calendar year fixed effects; $\alpha_a$ are scientist age fixed effects. Field fixed effects $\mu_f$ control for variation in patenting across fields $f$. Data include 107,313 patents by 29,954 STEM scientists who are married.

FIGURE 4 – LIFE CYCLE PRODUCTIVITY, PUBLICATIONS BY ACADEMIC SCIENTISTS

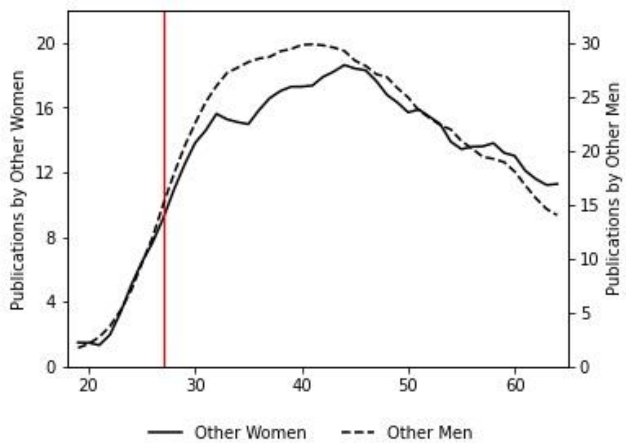
PANEL A: MOTHERS VS FATHERS



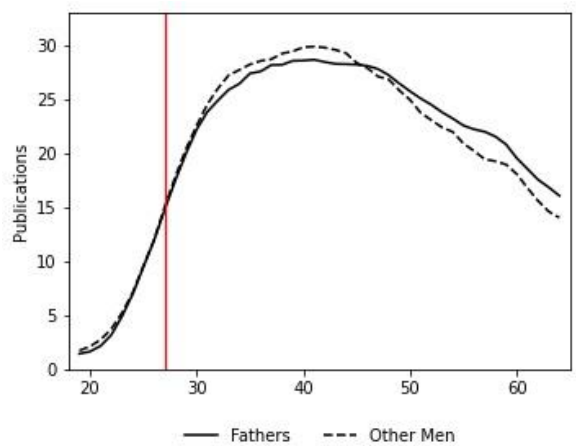

PANEL B: MOTHERS VS OTHER WOMEN




PANEL C: MEN VS WOMEN W/O CHILDREN

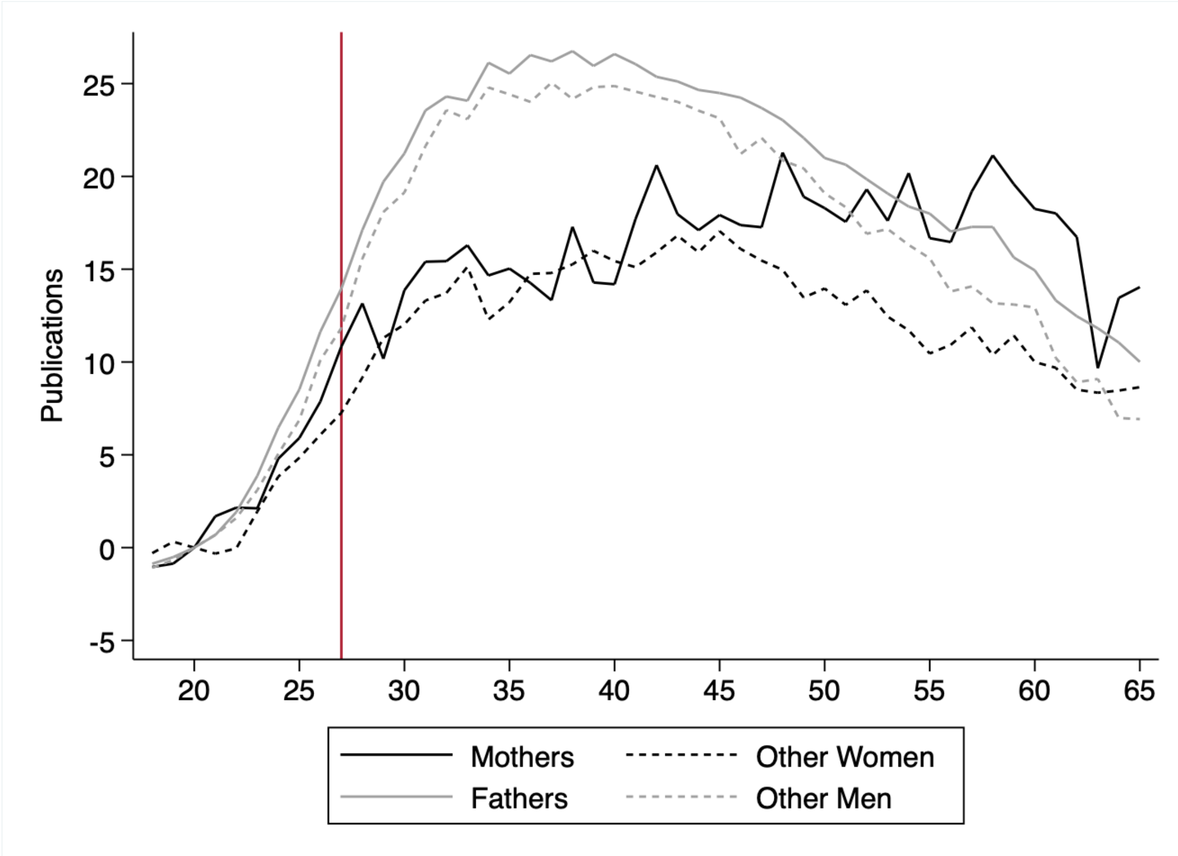



PANEL D: FATHERS VS OTHER MEN




*Notes:* Changes in productivity across the life cycle, measured by a three-year moving average of author-weighted publications. The vertical line at age 27 marks the median age of marriage for both female and male scientists. Data include 379,502 author-weighted publications by 52,946 academic scientists across all disciplines.

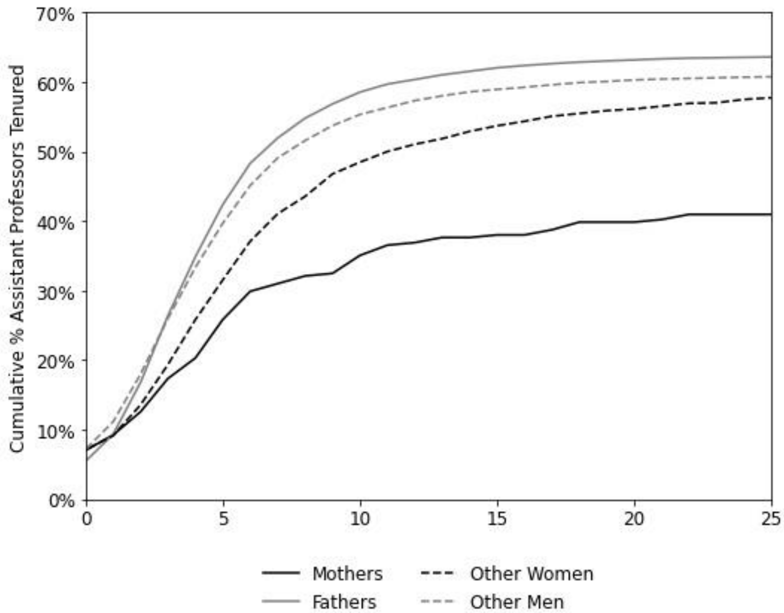
FIGURE 5 – AGE-VARYING ESTIMATES OF CHANGES IN SCIENTIFIC OUTPUT, PUBLICATIONS BY ACADEMIC SCIENTISTS



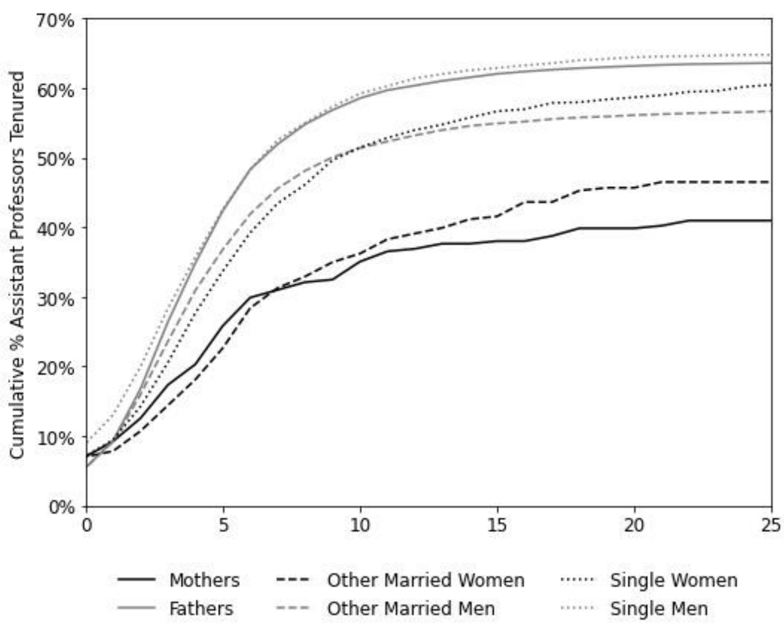

*Notes:* OLS estimates of $\beta_a^d$ for demographic $d$ (mothers, fathers, other women, and other men) in the equation $y_{iat}^d = \beta_a^d Age_i + \delta_t + \mu_f + \epsilon_{iat}$ where $y_{iat}^d$ are author-weighted publications per 100 scientists of demographic $d$ in age $a$ and calendar year $t$. The vertical line at age 27 marks the median age of marriage for both female and male scientists. The coefficient $\beta_a^d$ is a vector of age-varying estimates of publications at age $a$ by scientists of demographic $d$ compared with scientists in the same demographic at age 20. $\delta_t$ are calendar year fixed effects; $\mu_f$ are field fixed effects to control for variation in the number of publications across fields $f$. Data include 379,502 author-weighted publications by 52,946 academic scientists across all disciplines.

FIGURE 6 – SHARE OF ACADEMIC SCIENTISTS WITH TENURE, COUNTING FROM THEIR FIRST YEAR AS ASSISTANT PROFESSORS

PANEL A: PARENTS VS. OTHER SCIENTISTS




PANEL B: PARENTS VS. OTHER MARRIED AND UNMARRIED SCIENTISTS

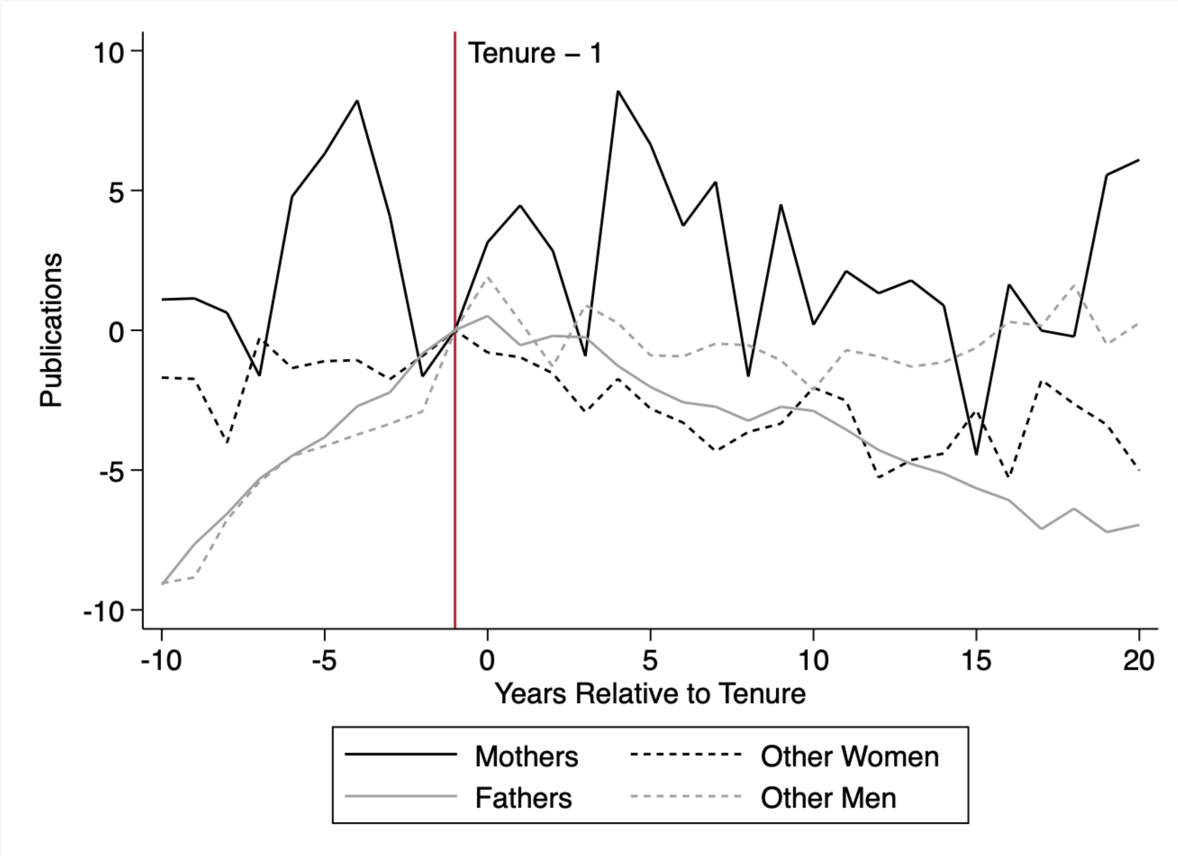



*Notes:* To examine differences in the speed of promotion across demographic groups we plot the cumulative share of assistant professors who attain tenure within *t* years after their first year as assistant professors. *Panel A* distinguishes parents from other scientists; *Panel B* further separates married from unmarried scientists. Data include 24,003 scientists across all disciplines who held a tenure-track assistant professor job.

FIGURE 7 – EVENT STUDIES OF CHANGES IN THE PROBABILITY OF TENURE AFTER MARRIAGE

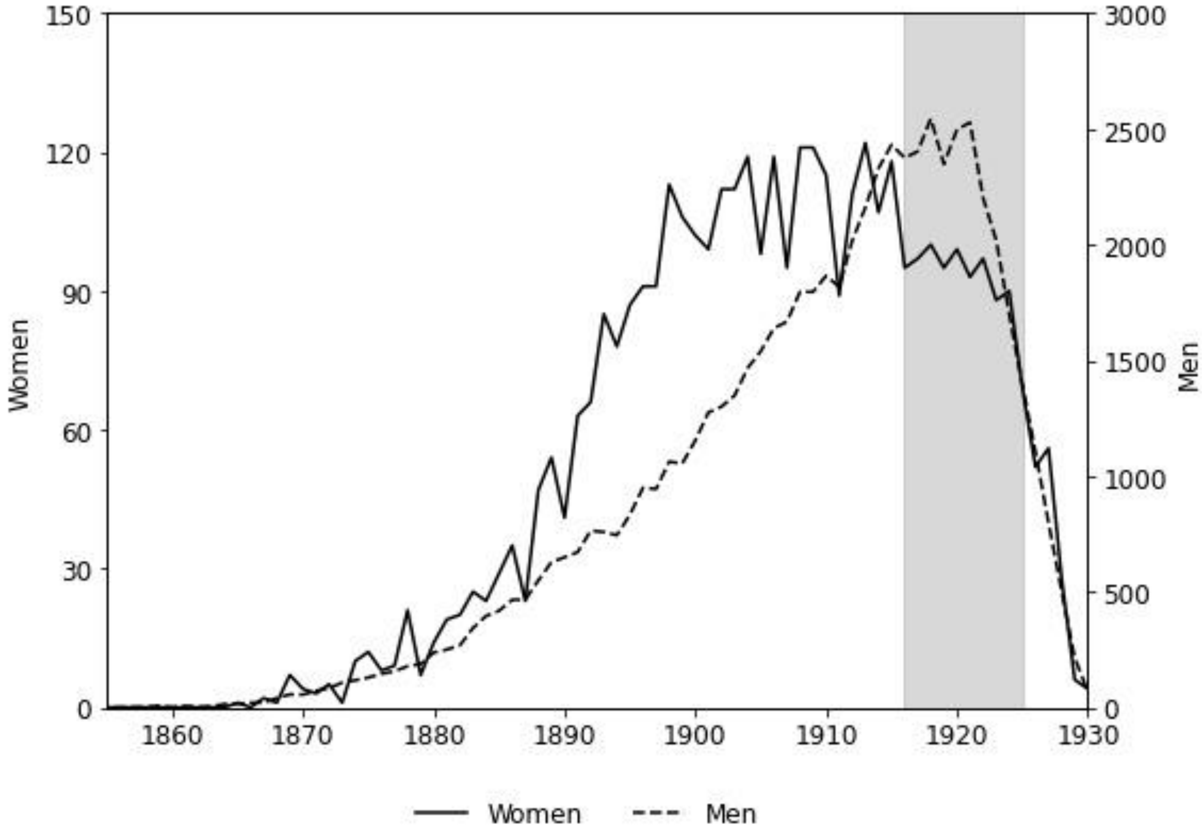

*Notes:* OLS estimates of $\beta_s^d$ for demographic $d$ (mothers, fathers, other married women, and other married men) in the equation $y_{ist}^d = \beta_s^d EventTime_i + \delta_t + \mu_f + \epsilon_{ist}$ where $y_{ist}^d$ equals 1 if scientist $i$ of demographic $d$ holds a tenured job at the rank of associate or full professor in year *s* relative to marriage and calendar year *t*. The coefficient $\beta_s^d$ is a vector of time-varying estimates for the probability that a scientist of demographic *d* holds a tenured job in year *s* after marriage, relative to the same probability for a scientist from the same demographic group one year before marriage. $\delta_t$ are calendar year fixed effects and $\mu_f$ are field fixed effects. Data include 19,143 married scientists across all disciplines who get a tenure-track assistant professor job.

FIGURE 8 – PRODUCTIVITY IN PUBLISHING BEFORE AND AFTER TENURE




*Notes:* OLS estimates of $\beta_s^d$ for demographic *d* (mothers, fathers, other women, and other men) in the equation $y_{ist}^d = \beta_s^d EventTime_i + \delta_t + \alpha_a + \mu_f + \epsilon_{ist}$ where $y_{ist}^d$ counts author-weighted publications per scientist $i$ of demographic *d* in year relative to tenure *s* and calendar year *t*. Productivity is measured by publications in event year *s* after tenure per 100 scientists in demographic group *d* and calendar year *t*. The coefficient $\beta_s^d$ is a vector of time-varying estimates of publications in event year *s* relative to tenure by scientists of demographic *d* compared with scientists in the same demographic one year before tenure. $\delta_t$ are calendar year fixed effects to capture variation in publishing intensity over time; $\alpha_a$ are age fixed effects to control for variation in publishing across the life cycle. Field fixed effects $\mu_f$ control for variation in publishing intensity across fields *f*. Data include 25,019 scientists who earned tenure.

FIGURE 9 – THE MISSING MOTHERS OF THE BABY BOOM: SCIENTISTS IN 1956 BY BIRTH YEAR




*Notes:* To examine changes in participation across birth cohorts we plot the number of scientists in 1956 per birth year. Our data cover 70,230 scientists born between 1850 and 1940, including 4,032 women and 66,198 men. The grey bar denotes the generation of baby boom parents: 22,934 scientists who were in their 20s during the baby boom.

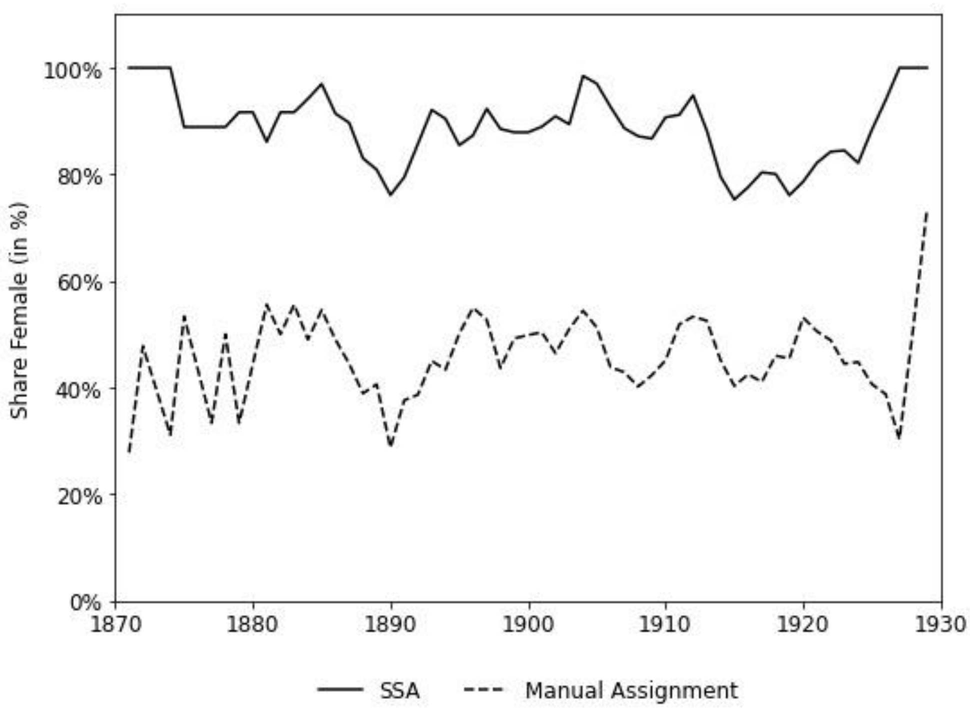
APPENDIX A: IDENTIFYING FEMALE SCIENTISTS

To determine the most accurate approach to identify female scientists, we use scientists who graduated from women's colleges (at a time when they only admitted women) as a benchmark. Starting with a list of women's colleges in the United States, we searched the websites of these colleges to check if (and when) the college has admitted men or has merged with a coeducational institution. Using this information, we create an indicator *WCollege* which equals 1 for scientists who earned a degree at a women's college when that college only admitted women. In the next step we compare two alternative methods of assigning scientists to gender:

1) *Manual Assignment.* We asked the data typists who hand-entered biographies from the hard copies of the MoS (1921 and 1956) to flag names of female scientists. They identified 2,674 of 82,094 American scientists (3.3%) in 1956 as women and 79,420 (96.7%) as men.
2) *Gender of Names in the Social Security Administration Data, 1880-2011*. A key issue with manual assignment is that it relies on naming practices today, which differ from those in the birth years of scientists in the 1950s. To address this issue, we create an alternative measure using gender frequencies in the universe of first name-gender pairings in the records of the US Social Security Administration between 1880 and 2011 through Python's *gender-detector* package 0.1.0 (https://pypi.org/project/gender-detector/: accessed June 25, 2020). By this measure, a scientist is identified as female if at least 95 percent of people with that name in the historical SSA records identify as female. Using this measure, 4,412 of 82,094 (5.4%) are identified as female.

Comparing the two measures with graduates from women's colleges, we find that the SSA data assigns significantly fewer women as men. 87.6% of scientists who attended women's colleges are recognized as female scientists by the SSA assignment compared with just 46.3% by hand assignment. The share of false negatives is stable over time (Appendix Figure A1).

FIGURE A1 - SHARE OF GRADUATES OF WOMEN'S COLLEGES IDENTIFIED AS WOMEN



## Appendix B: Matching Faculty with the Census and the MoS

To examine whether access to childcare improves a mother's odds of surviving in science, we match scientists who were on the faculty of Columbia University in 1943-45 with records in the US Census (1940) and the MoS (1956). Information on household income and live-in servants in the 1940 Census allows us to measure differences in access to childcare.

1) First, we digitize faculty records of Columbia University for 1943-1945 (https://babel.hathitrust.org/cgi/pt?id=nnc2.ark:/13960/t7mp5qv2z&view=1up&seq=7), immediately before the baby boom. To establish a high-quality match with the census, we extract information on the scientist's age and place of residence from the faculty directories.
    a. First, we estimate a faculty member's approximate age in 1940, using the grant year of their undergraduate and graduate degrees. In the MoS (1956), the median scientist was 23 years old when receiving their undergraduate degree. If the award year of the undergraduate degree is unknown, we use ages of 20-35 for the grant year of a master's degree and 23-40 for a PhD to identify potential matches.
    b. Information in the directories on the scientist's university or place of work in 1940 allows us to determine their county of residence in 1940. For example, the entry for Harold Hotelling below reports that Hotelling came to Columbia in 1931 and was a Professor of Economics there in 1943-45, which means that he was employed in New York County in 1940.

       Harold Hotelling, 1931 . . . . . . . . . . . . . . . *Professor of Economics*
       A.B., University of Washington, 1919 ; M.S., 1921 ; Ph.D., Princeton, 1924.

2) *Algorithmic matching*: Using the scientist's name, their county of residence in 1940, and their approximate age in 1940, we use Python to identify 621 potential matches for the 2,446 Columbia faculty in 1943-45 in the 1940 Census. We constrain matches to those whose first and last names are within a 0.1 Jaro-Winkler distance of one of the 2,446 faculty members and who lived in the same county in 1940.
3) *Manual Data Checks*: Using occupations, education, and birth years, we manually check all possible matches and identify 539 verified matches between Columbia faculty and the census of 1940; 131 of these matched scientists are included in the MoS (1956).
4) *Matching Faculty Members with the MoS (1956)*: Using the scientist's name and their career history in the MoS, we create a Python algorithm that identifies scientists in the MoS (1956) who worked at Columbia between 1943 and 1945. Among 2,446 faculty members at Columbia, 378 survived to enter the MoS in 1956 (15.5%). Linked census records are available for 131 of these 378 surviving faculty (34.7%).

TABLE A1 – INTENSITY ESTIMATES: DO SCIENTISTS WITH MORE CHILDREN PRODUCE MORE PATENTS?

| | Patents per 1,000 scientists | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Female | -58.698*** | -56.282*** | -52.455*** | -24.319*** | -25.037*** | -21.883*** |
| | (1.731) | (1.742) | (1.560) | (0.674) | (0.672) | (0.609) |
| 1 Child | 16.686*** | 18.220*** | 15.583*** | 10.946*** | 10.027*** | 9.907*** |
| | (1.848) | (1.859) | (1.710) | (0.976) | (0.975) | (0.898) |
| 2 Children | 18.276*** | 19.503*** | 17.173*** | 12.322*** | 11.397*** | 11.234*** |
| | (1.684) | (1.648) | (1.487) | (0.827) | (0.826) | (0.766) |
| 3+ Children | 17.814*** | 18.857*** | 17.123*** | 11.951*** | 11.090*** | 11.169*** |
| | (1.684) | (1.664) | (1.567) | (0.858) | (0.847) | (0.795) |
| Female*1 Child | -22.842*** | -25.898*** | -26.649*** | -12.345*** | -12.013*** | -12.810*** |
| | (3.738) | (3.862) | (3.474) | (1.387) | (1.406) | (1.278) |
| Female*2 Children | 5.346 | 4.898 | 1.270 | -6.388*** | -5.605** | -6.797*** |
| | (7.634) | (7.613) | (7.304) | (2.326) | (2.318) | (2.184) |
| Female*3+ Children | -13.161*** | -15.816*** | -15.387*** | -4.700*** | -4.286*** | -6.504*** |
| | (3.309) | (3.489) | (3.060) | (1.196) | (1.230) | (1.107) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Birth Year FE | Yes | No | Yes | Yes | No | Yes |
| Age FE | No | Yes | No | No | Yes | No |
| Field FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Disciplines | STEM | STEM | STEM | All | All | All |
| Scientists' age | 18-65 | 18-65 | 18-80 | 18-65 | 18-65 | 18-80 |
| N (scientists x years) | 1,204,592 | 1,204,592 | 1,298,053 | 2,391,179 | 2,391,179 | 2,591,524 |
| Pre-baby boom mean | 88.107 | 88.107 | 87.524 | 46.063 | 46.063 | 45.792 |

*** denotes significance at the 1-percent level, ** at the 5-percent level, and * at the 10-percent level

*Notes:* OLS estimates of differences in the number of patents issued to 1,000 scientists in different demographic groups per year between 1930 and 1970. $Female_i$ is an indicator for women; $x\ Child_i$ indicates parents with $x$ children. Robust standard errors in parentheses. Columns (1)-(3) present estimates for the physical sciences (STEM). Columns (4)-(6) include scientists across all disciplines, including STEM and the biological and social sciences.

TABLE A2 – INTENSITY ESTIMATES: DO SCIENTISTS WITH MORE CHILDREN PUBLISH MORE?

| | Publications (1-6) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Female | -6.942*** | -7.371*** | -6.468*** | -8.109*** | -8.201*** | -7.348*** |
| | (0.280) | (0.277) | (0.254) | (0.181) | (0.179) | (0.166) |
| 1 Child | 0.682*** | 0.221 | 0.731*** | -0.038 | -0.046 | -0.020 |
| | (0.176) | (0.175) | (0.165) | (0.137) | (0.136) | (0.128) |
| 2 Children | 0.470*** | -0.457*** | 0.505*** | 0.119 | -0.384*** | 0.167 |
| | (0.149) | (0.147) | (0.140) | (0.117) | (0.116) | (0.109) |
| 3+ Children | 0.897*** | -0.206 | 0.906*** | 0.564*** | -0.121 | 0.655*** |
| | (0.157) | (0.153) | (0.147) | (0.122) | (0121) | (0.114) |
| Female*1 Child | 1.379 | 1.923** | 1.824** | -0.222 | -0.340 | -0.366 |
| | (0.875) | (0.876) | (0.860) | (0.450) | (0.449) | (0.429) |
| Female*2 Children | -1.294 | -1.433* | -1.530** | -0.947** | -1.021** | -1.249*** |
| | (0.794) | (0.789) | (0.755) | (0.473) | (0.471) | (0.448) |
| Female*3+ Children | -6.271*** | -5.838*** | -6.286*** | -2.262*** | -2.138*** | -2.814*** |
| | (0.935) | (0.928) | (0.872) | (0.584) | (0.582) | (0.556) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Birth Year FE | Yes | No | Yes | Yes | No | Yes |
| Age FE | No | Yes | No | No | Yes | No |
| Field FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Disciplines | STEM | STEM | STEM | All | All | All |
| Scientists' age | 18-65 | 18-65 | 18-80 | 18-65 | 18-65 | 18-80 |
| N (scientists x years) | 1,204,592 | 1,204,592 | 1,298,053 | 2,391,179 | 2,391,179 | 2,591,524 |
| Pre-baby boom mean | 11.189 | 11.189 | 11.208 | 15.832 | 15.832 | 15.862 |

*** denotes significance at the 1-percent level, ** at the 5-percent level, and * at the 10-percent level

*Notes:* OLS estimates of differences in the number of author-weighted publications issued per year between 1930 and 1970 to 100 scientists (columns 1-6) and author-weighted citations per scientist (columns 7-8) in different demographic groups. $Female_i$ is an indicator for women; the variables $x\ Child_i$ indicate parents with $x$ children in 1956. Robust standard errors in parentheses. Columns (1-3) present estimates for the physical sciences (STEM). Columns (4)-(6) include scientists across all disciplines, including STEM and the biological and social sciences.

TABLE A3 – PRODUCTIVITY DIFFERENCES ACROSS DEMOGRAPHIC GROUPS: INVENTOR-WEIGHTED PATENTS

| | Patents per 1,000 scientists | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Female | -52.454*** | -50.583*** | -46.860*** | -21.837*** | -22.532*** | -19.662*** |
| | (1.495) | (1.511) | (1.349) | (0.595) | (0.593) | (0.538) |
| Parent | 16.005*** | 16.350*** | 15.121*** | 10.554*** | 9.531*** | 9.682*** |
| | (1.217) | (1.250) | (1.127) | (0.615) | (0.615) | (0.566) |
| Female*Parent | -6.687* | -8.025** | -10.129*** | -6.818*** | -6.288*** | -7.538*** |
| | (3.689) | (3.711) | (3.474) | (1.172) | (1.173) | (1.092) |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Birth year FE | Yes | No | Yes | Yes | No | Yes |
| Age FE | No | Yes | No | No | Yes | No |
| Field FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Disciplines | STEM | STEM | STEM | All | All | All |
| Scientists' age | 18-65 | 18-65 | 18-80 | 18-65 | 18-65 | 18-80 |
| N (scientists x years) | 1,204,592 | 1,204,592 | 1,298,053 | 2,391,179 | 2,391,179 | 2,591,524 |
| Pre-baby boom mean | 79.545 | 79.545 | 79.026 | 41.514 | 41.514 | 41.273 |

*** denotes significance at the 1-percent level, ** at the 5-percent level, and * at the 10-percent level

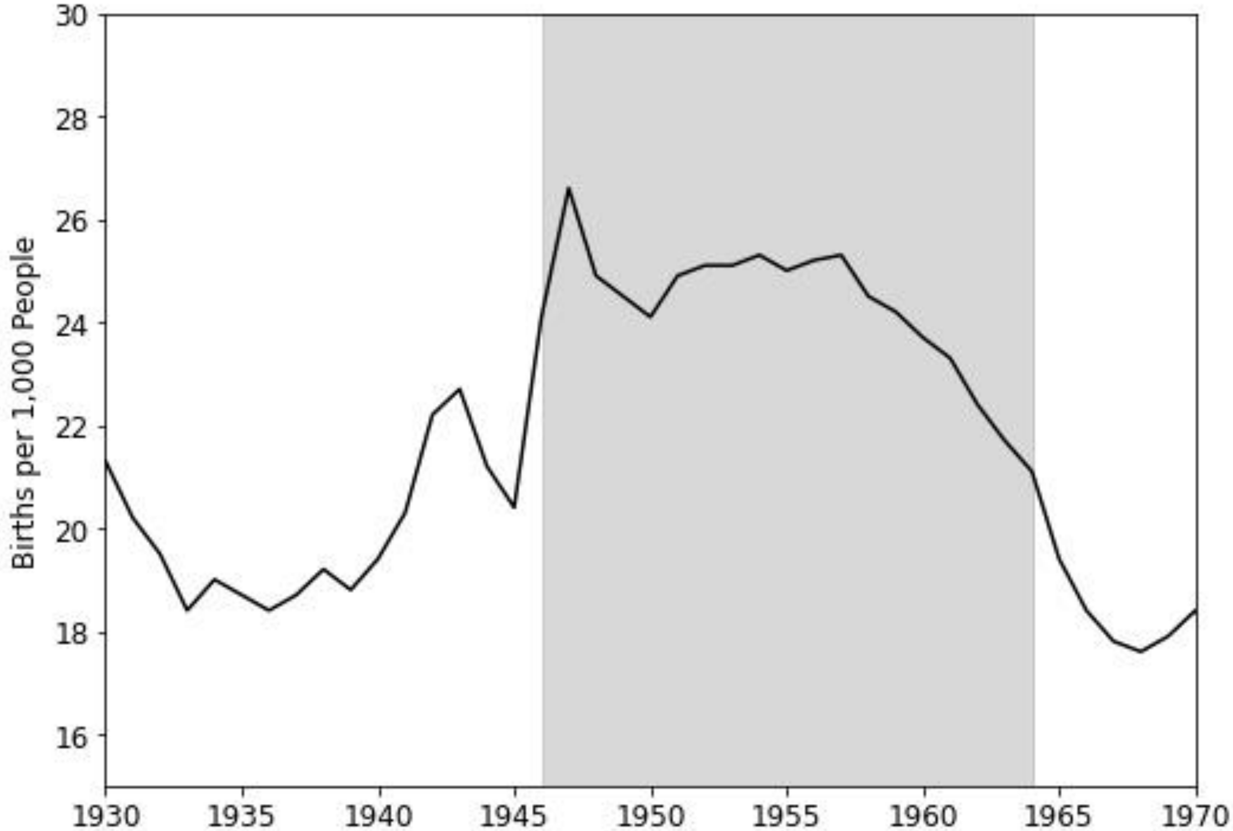
*Notes:* OLS estimates of differences in the number of inventor-weighted patents issued to 1,000 scientists in different demographic groups per year between 1930 and 1970. $Female_i$ is an indicator for women and $Parent_i$ indicates parents. Robust standard errors in parentheses. Columns (1)-(3) present estimates for the physical sciences (STEM). Columns (4)-(6) include scientists across all disciplines, including STEM and the biological and social sciences.

TABLE A4 – SELECTION INTO FIELDS: DID MOTHERS SELECT INTO LESS PRODUCTIVE FIELDS?

| | Mothers | Women without children | | | Fathers | Men without children | | |
|---|---|---|---|---|---|---|---|---|
| | | All | Married | Single | | All | Married | Single |
| Patents | -0.1697 | -0.1688 | -0.1215 | -0.1784 | 0.0006 | -0.0464 | -0.0271 | -0.0729 |
| Publications | 0.0983 | 0.0805 | 0.1355 | 0.0628 | -0.0726 | -0.0710 | -0.0549 | -0.0852 |
| N all scientists | 892 | 3,140 | 734 | 2,406 | 48,987 | 7,211 | 8,933 | 8,278 |
| N STEM scientists | 252 | 920 | 227 | 693 | 25,829 | 8,367 | 4,711 | 3,656 |

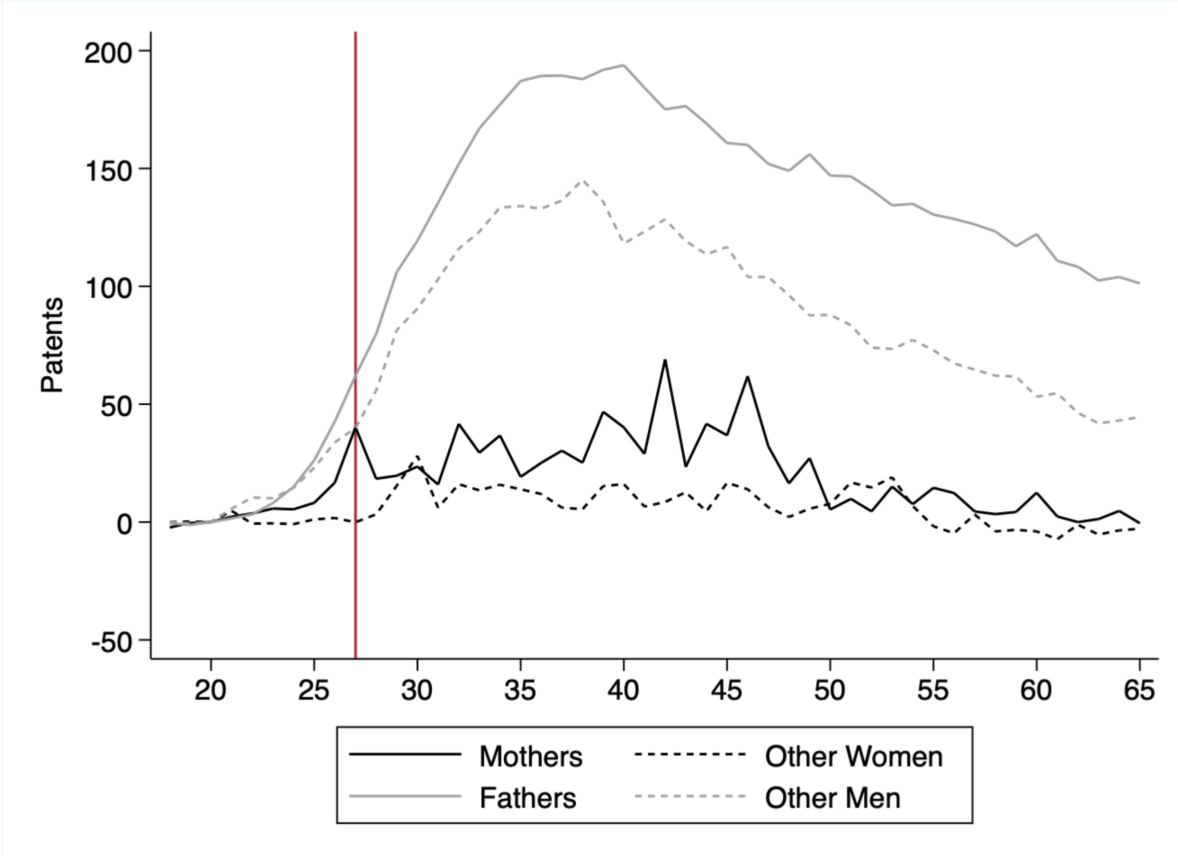
*Notes:* Correlation coefficients between the share of scientists from each demographic group and the average number of patents and publications across 100 research fields. Research fields are defined by applying a *k*-means matching algorithm to the research topics of scientists, implementing a method from Moser and San (2020).

FIGURE A2 – US BIRTHS PER 1,000 PEOPLE FROM 1930 TO 1970




*Notes:* US births per 1,000 people from the Center for Disease Control and Prevention (2003). Birth years in grey mark the official period of the baby boom, as defined by the US Census.

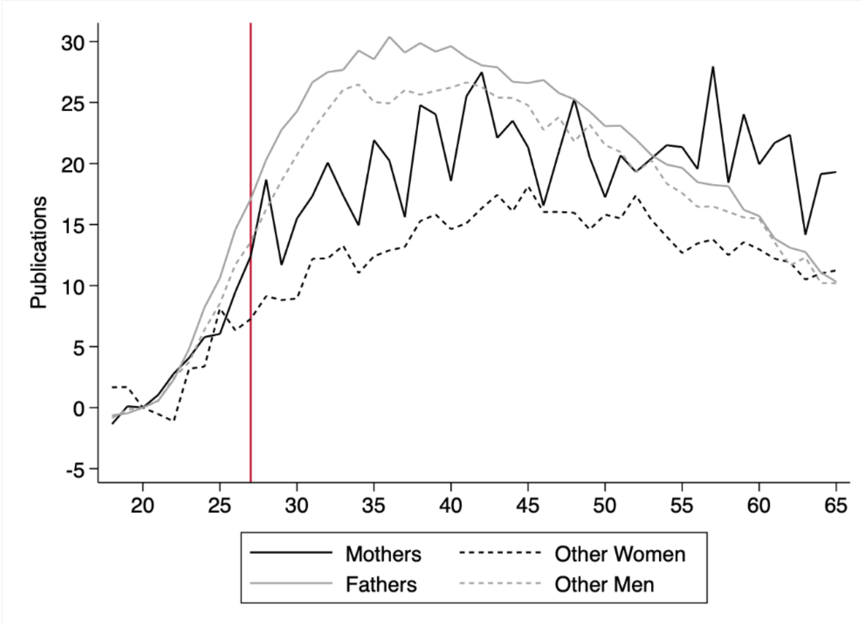
FIGURE A3 – AGE-VARYING ESTIMATES OF PRODUCTIVITY, INVENTOR-WEIGHTED PATENTS



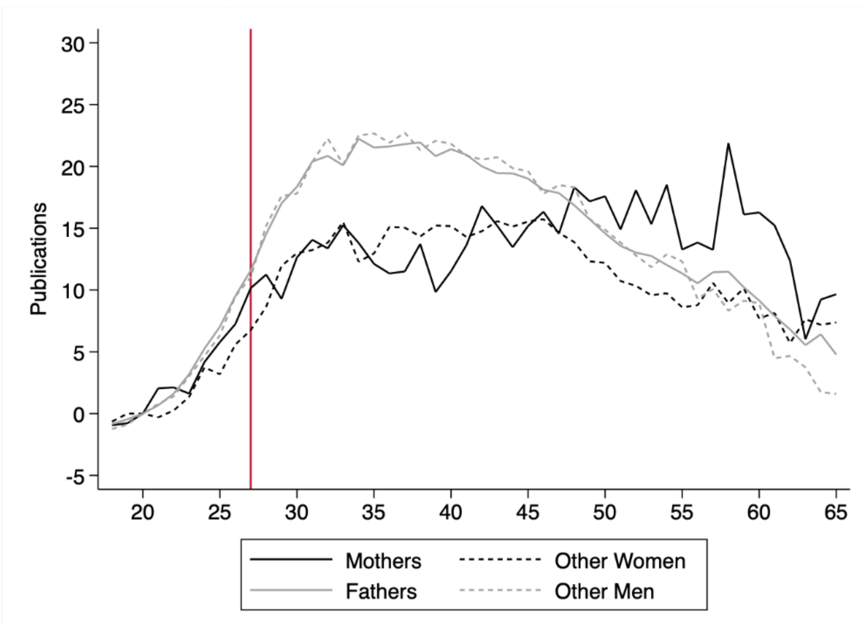

*Notes:* OLS estimates of $\beta_a^d$ for demographic $d$ (mothers, fathers, other women, and other men) in the equation $y_{iat}^d = \beta_a^d Age_i + \delta_t + \mu_f + \epsilon_{iat}$ where $y_{iat}^d$ counts patents per 1,000 scientists of demographic $d$ in age $a$ and calendar year $t$ – divided by the total number of scientists who are listed as inventors on the patent. The vertical line at age 27 marks the median age of marriage for both female and male scientists. The coefficient $\beta_a^d$ is a vector of age-varying estimates of inventions created by scientists of age $a$ and demographic $d$ compared with scientists in the same demographic at age 20. $\delta_t$ are calendar year fixed effects to capture variation in patenting over time, and $\mu_f$ are field fixed effects. Data include 35,368 STEM scientists.

FIGURE A4 – AGE-VARYING ESTIMATES OF PRODUCTIVITY IN TERMS OF PUBLICATIONS

PANEL A: ACADEMIC SCIENTISTS WITH TENURE



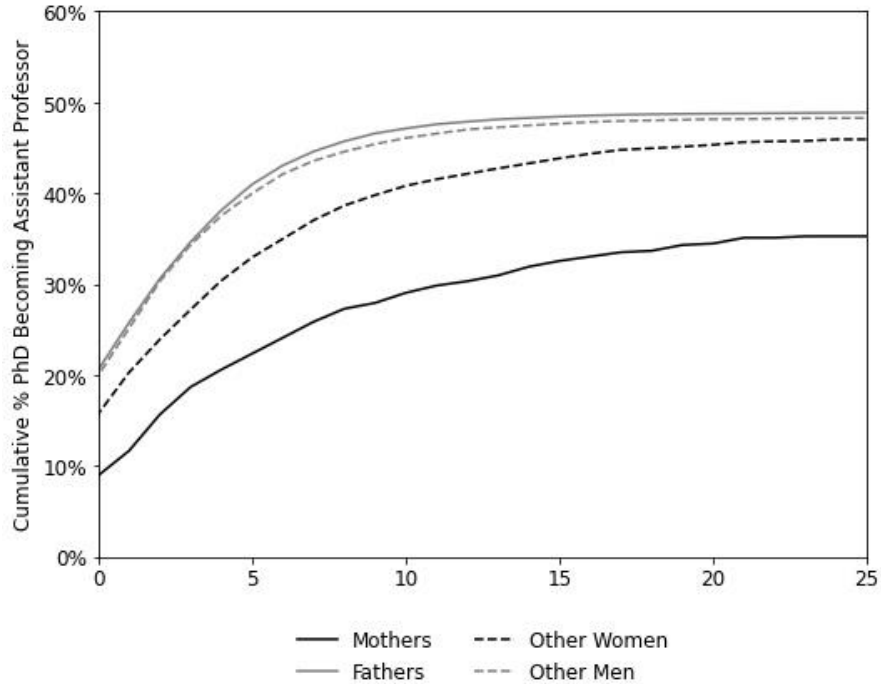

PANEL B: ACADEMIC SCIENTISTS WITHOUT TENURE



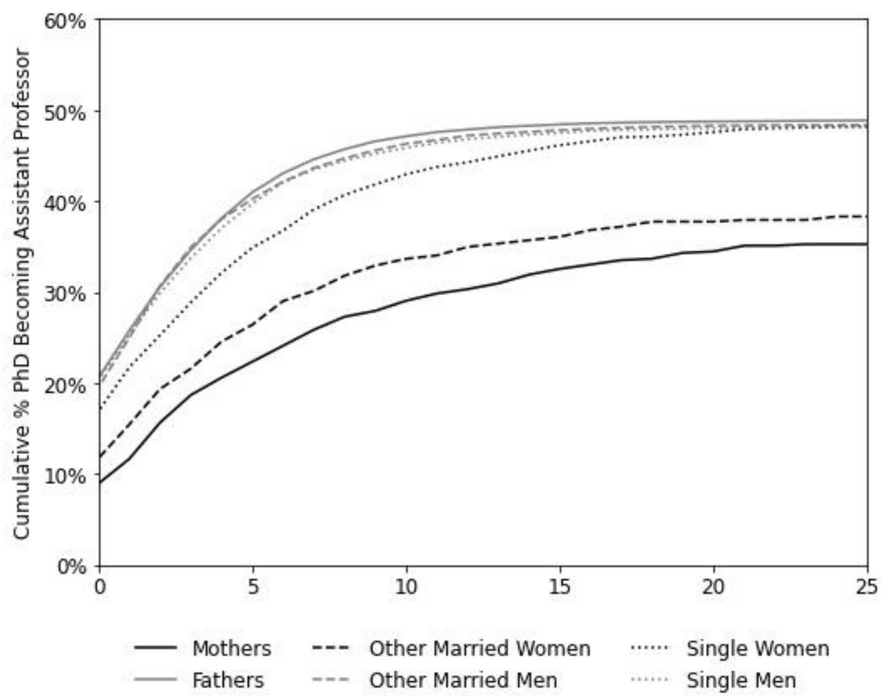

*Notes:* OLS estimates of $\beta_a^d$ for demographic *d* (mothers, fathers, other women, and other men) in the equation $y_{iat}^d = \beta_a^d Age_i + \delta_t + \mu_f + \epsilon_{iat}$ where $y_{iat}^d$ are publications per 100 scientists of demographic *d* in age *a* and calendar year *t*. The vertical line at age 27 marks the median age of marriage for both female and male scientists. The coefficient $\beta_a^d$ is a vector of age-varying estimates of publications by scientists of age *a* and demographic *d* compared with the same demographic at age 20. $\delta_t$ are calendar year fixed effects, and $\mu_f$ are field fixed effects. Data include 379,502 publications by 52,946 academic scientists across all fields. Panel A reports estimates for 25,019 academic scientists who held a tenured job; Panel B reports estimates for 27,927 academic scientists without getting tenure.

FIGURE A5 – TIME TO GET A TENURE-TRACK JOB

PANEL A: PARENTS VS. OTHER SCIENTISTS




PANEL B: BY MARITAL STATUS




*Notes:* To examine differences in time it took scientists to get a tenure-track job, we plot the cumulative share of scientists who became tenure-track assistant professors within *t* years of getting their PhD. *Panel A* reports this difference for parents compared with other scientists; *Panel B* further distinguishes married from single scientists. Data include 41,265 academic PhD scientists across all disciplines.

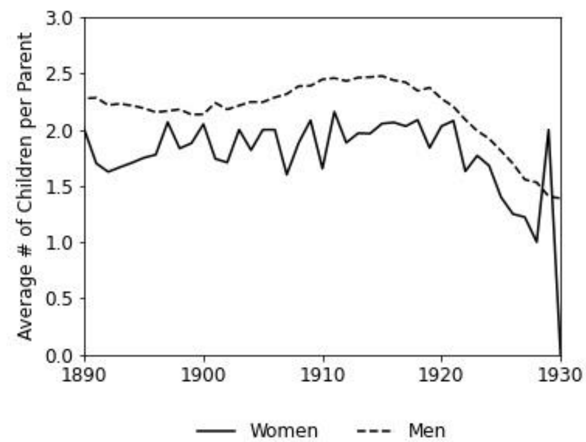
FIGURE A6 – CHANGES IN MARRIAGE RATES AND CHILDREN ACROSS BIRTH COHORTS

PANEL A: SHARE OF MARRIED SCIENTISTS


PANEL B: AGE AT MARRIAGE


PANEL C: SHARE OF PARENTS

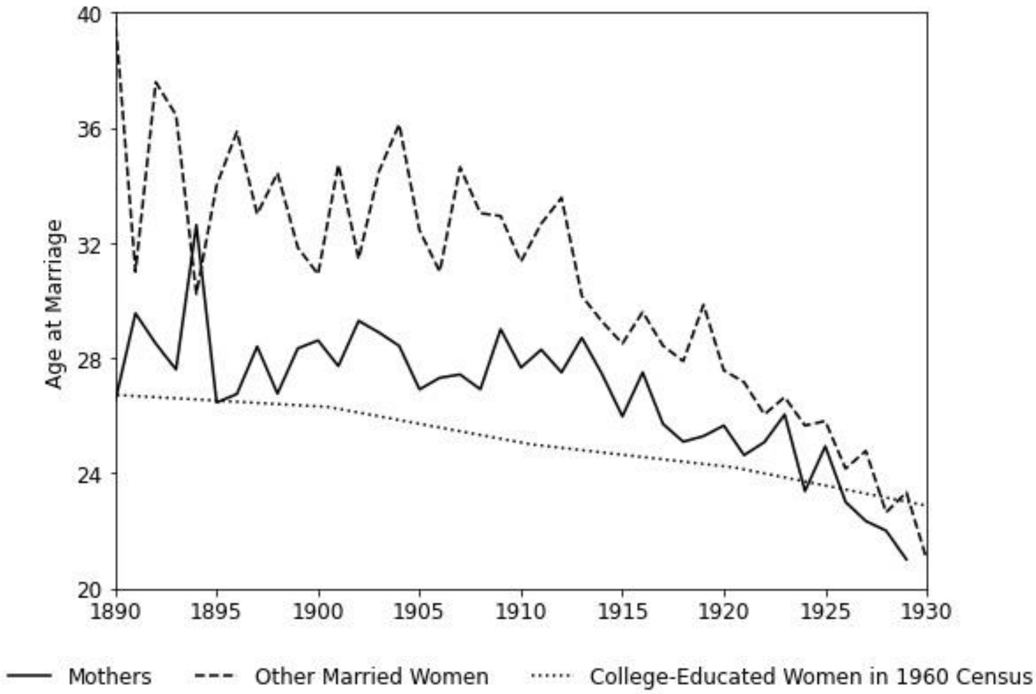

PANEL D: NUMBER OF CHILDREN PER PARENT



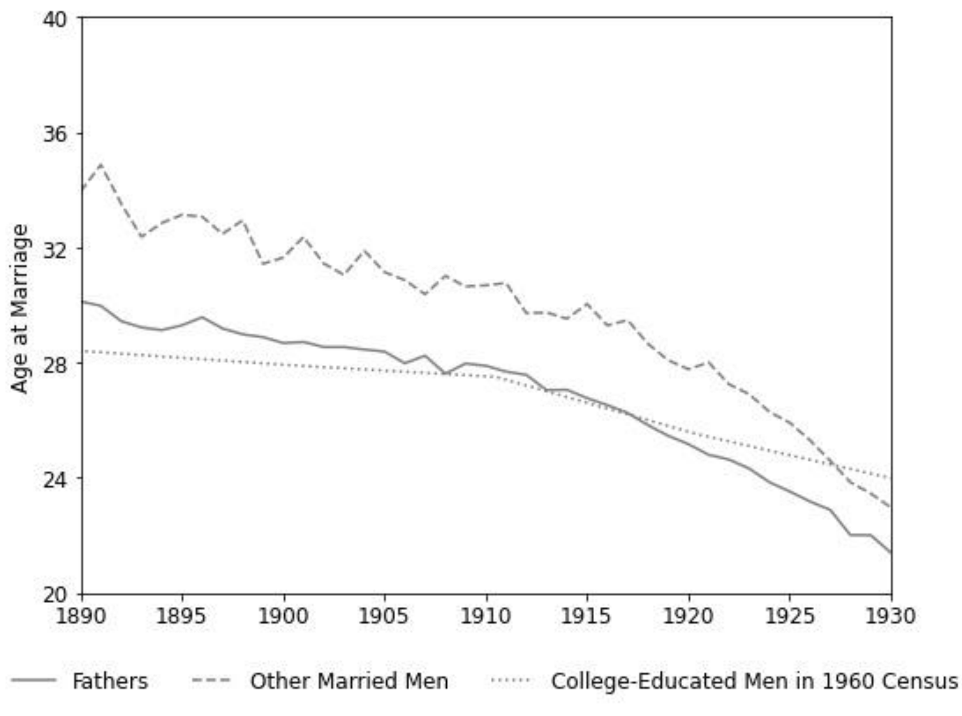

*Notes:* To investigate selection into marriage and parenting, we examine changes across birth cohorts in the share of scientists who decided to marry and have children. *Panel A* plots the share of scientists who were married, *Panel B* shows the mean age at which scientists got married, *Panel C* plots the share of scientists (in %) who are parents, and *Panel D* reports the average number of children per parent. Data include 70,230 scientists with known birth years and gender.

FIGURE A7 – CHANGES IN THE AGE AT MARRIAGE ACROSS BIRTH COHORTS

PANEL A: WOMEN

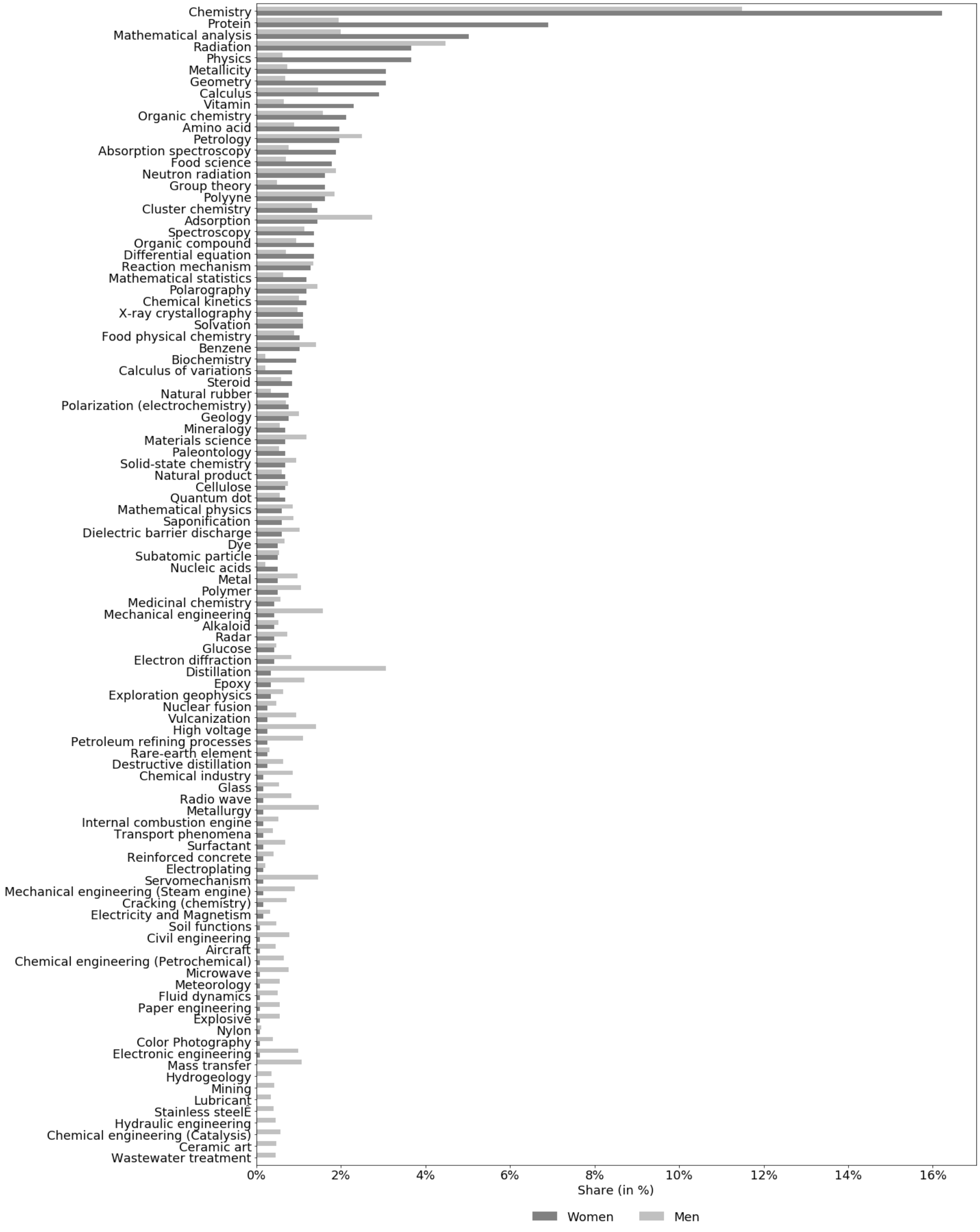



PANEL B: MEN




*Notes:* To compare changes in the timing of marriage for scientists and other college-educated Americans, we plot the mean age at marriage for 57,336 scientists in the MoS against that of college-educated Americans in the census of 1960 (U.S. Census Bureau. *Estimated Median Age at First Marriage, by Sex: 1880 to Present*).

FIGURE A8 – DISTRIBUTION OF SCIENTISTS ACROSS FIELDS: WOMEN VS MEN




*Notes:* To investigate whether women avoided fields in the "hard sciences" like physics or mathematics, we compare the distribution of male and female scientists across fields. Scientists are assigned to unique fields, implementing *k*-means matching as in Moser and San (2020).

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