WOMEN IN SCIENCE
LESSONS FROM THE BABY BOOM

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How do children affect scientific output, promotions, and gender inequality in science? We investigate this question by analyzing 82,094 biographies – matched with patents and publications – in 1956, at the height of the baby boom. Examining life cycle patterns of productivity, we find that mothers' productivity peaks in their early 40s, long after other scientists have started to decline. Event studies of marriage show that mothers become more productive 15 years after marriage, when children are in their teens. Differences in the timing of productivity have important implications for tenure. Just 27% of mothers who are academics achieve tenure, compared with 48% of fathers and 46% of other women. Examining selection, we find that women are half as likely to survive in science, but more likely to hold a PhD, and much less likely to marry and have children compared with men. Output data show that mothers who survive in science are extremely positively selected. Employment data indicate that a generation of women was lost to American science during the baby boom.

KEYWORDS: SCIENCE, INNOVATION, GENDER INEQUALITY, AND BABY BOOM.

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Women continue to be severely underrepresented in science,[1] and children are a possible cause. According to the American Time Use Survey, mothers spend roughly 50% more time caring for children than fathers.[2] During the COVID-19 pandemic, mothers with young children reduced their work hours four to five times as much as fathers (Collins 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 hours worked today may affect the careers of working mothers for years to come (e.g., Alon et al. 2020). Existing research has found that the unequal burden of parenting contributes to the persistent gender gap in earnings (e.g., Bertrand, Goldin, and Katz 2010, Adda, Dustmann, Stevens 2017; Klevens, Landais, and Soogard 2019). Less is known about the effects of children on life-cycle patterns of *productivity*.

Using linked scientist-level data on patents and publications, this paper investigates how children influence scientific productivity over the entire life cycle of a scientist and how such differences affect tenure decisions and women's participation in science. Our analyses explore detailed biographic data for 82,094 American scientists in 1956, at the height of the baby boom (1946-1964). Focusing on the baby boom allows us to examine the effects of children at a time when the burden of childcare fell squarely on women and couples had children soon after they married.

Patent data show that mothers experience a major productivity boost in their late 30s and early 40s, long after other scientists have started to decline. Mothers' patents (and publications) suffer in their late 20s and begin to recover after age 35. Mothers' reach top productivity at age 42, 7 years after the output of fathers has peaked at age 35. On average, mothers patent substantially less than fathers and slightly more than other women, suggesting that mothers who survive in science may be positively selected. Gender differences in productivity are strongest in STEM and less pronounced in the biological and social sciences, while differences between parents and other scientists are comparable across disciplines.

[1] Eight in ten women and minority students who enroll in science, technology, engineering and mathematics (STEM) drop out of college or switch to another undergraduate degree (Waldrop 2015). Women comprise a minority of senior staff in science, are promoted more slowly (National Academy of Sciences 2006) and are more likely to leave careers in STEM (Shaw and Stanton 2012). Some of this attrition may be due to the lack of role models among faculty (Porter and Serra 2020) and in teaching materials (Stevenson and Zlotnik 2018), discrimination in hiring, glass ceilings in promotions (e.g., Altonji and Blank 1999; McDowell, Singell, and Ziliak 1999), and inequity in salary and support (Settles et al. 1996; Sonnert and Holton 1996).

[2] U.S. Bureau of Labor Statistics (2020). Women do more housework and childcare even when they earn more (Besen-Cassino and Cassino 2014) and when their husbands are unemployed (van der Lippe, Treas, Norbutas 2018).

To investigate the causal effects of parenting on output, we estimate event studies of changes in patenting after marriage. Baby boom families had children soon after they married, allowing us to use marriage as a proxy for the birth of the first child. Methodologically, the event study approach exploits the fact that changes in output caused by the birth of a child occur sharply, while other determinants of productivity, such as a scientist's preference for leisure, influence output more smoothly. Another key benefit of the event study approach is that it allows us to exploit the long-run nature of the data and examine changes in scientific productivity across the complete life cycle of a scientist, including the time when their children are older.

Event studies of changes in patenting after marriage show that mothers produce fewer inventions in the first decade of marriage but experience a large and sustained boost 15 years into the marriage. For example, mothers produce 6.8 additional patents per 100 scientists after 20 years of marriage compared with themselves one year before marrying. This late-in-life increase in productivity is unique to mothers. Output by other married women stays flat after age 35, and the productivity of fathers (and other married men) increases significantly in the first 10 years after marriage but declines afterwards. Importantly, there is no evidence that mothers are less productive than other women before marriage. In fact, mothers produce more patents up to age 27 (the median age of marriage for female scientists) compared with other married women.

Why does mothers' productivity increase late in life and late in marriage? One possibility is that their heightened productivity 15 years after marriage reflects pent-up research ideas that mothers accumulate while taking care of children. This hypothesis, however, is at odds with fundamental results of high returns to experience in the labor market (e.g., Jacobson, Lalonde, and Sullivan 1993; Neal 1995; Jarosch 2015), as well as with skill depreciation (McDowell 1982). A simpler, more plausible explanation is that children require less work as they grow up (e.g., BLS 2020), leaving mothers more time to do research.

Analyses of publications confirm that mothers are less productive in their late 20s and early 30s but experience a substantial increase productivity in their late 30s and early 40s; data on promotions show that this unique life-cycle pattern of productivity is associated with low rates of tenure. Only 27% of mothers achieve tenure, compared with 48% of fathers and 46% of other women. Data on the speed of promotions show that, counting from their first year as an assistant professor, mothers have comparable tenure rates for the first five years, but fall behind after that and never catch up again to other scientists.

Tenure decisions use past productivity to predict future productivity. If these bets are right, there should be only minor differences in output across demographic groups after tenure. Yet, publication data show that mothers who get tenure publish more after tenure, while the productivity of all other demographic groups declines. These results point to structural problems or biases in the tenure process that disadvantage mothers.

To help interpret these and other findings, we investigate several dimensions of selection: into the PhD, tenure track jobs, marriage, parenting, research fields, and survival as a scientist. Despite powerful barriers to entry, we find that female scientists were more likely to hold a PhD compared with men.[3] Importantly, there is no evidence that mothers were less productive than other women. For instance, we find that married women produced more patents and more publications than single women by age 27, the median age of marriage. Yet, mothers were much less likely to obtain tenure track positions, both compared with other women and with men. Marriage data for scientists show that women were less than half as likely to marry and one third as likely to have children compared with men. Matching scientists with pre-baby boom faculty directories show that women were half as likely to survive in science compared with men.

In a final section, we examine the aggregate effects of the baby boom on participation and gender inequality in science. Employment records indicate that the baby boom created a lost generation of women in science. Women who were of child-bearing age during the baby boom are missing among American scientists in 1956 and among the scientists who entered during the baby boom. The "mothers of the baby boom" and their contributions were lost to American science. Moreover, their loss may contribute to the dearth of female role models that affects science today.

Our analysis contributes to the rich literature documenting persistent gender inequality in science (e.g., National Academy of Science. 2006). Despite major advances in gender equality since the 1950s,[4] women continue to be underrepresented in science and particularly in STEM. Huang et al (2020), for example, show that women continue to have shorter career and are more

[3] 84% of female scientists had earned a PhD, compared with 78% of male scientists. Parents of both genders were slightly less likely to hold a PhD compared with scientists of the same gender without kids.

[4] Notably, these advances have been linked to the introduction of oral contraceptives (in the form of the birth control "pill") which allowed women to avoid or 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 age 21 reduced the likelihood of a first birth before age 22, increased female labor force participation, and raised the number of annual hours worked.

likely to drop out of publishing in STEM. During the first wave of COVID-19 a survey in April 2020 found that female scientists with young children had suffered the most dramatic decline in their ability to devote to research (Myers et al 2020).[5] These findings highlight the urgency for understanding the effects of children on women's participation in science.

Our research adds new evidence on productivity, and more specifically on the *timing* of productivity, to existing analyses of the impact of children on the gender gap (e.g., Bertrand, Goldin, and Katz 2010). Klevens, Landais, and Soogard (2019) find that the share of earnings inequality that is due to children has increased over time.[6] Our research complements analyses of gender inequality by investigating the productivity effects of children and by linking productivity to decisions on tenure and participation.

I. Historical Background

After the end of World War II, more Americans than ever married, married early, had children, and stayed married. In 1930, the median American woman had first married at age 21.3; by 1950, the median age of marriage had dropped by a full year to 20.3. In 1960, only 27.4% of American 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.

1.1. The Baby Boom (1946-1964)

The combination of these factors led to a dramatic increase in births from 1946 to 1964, during the American "baby boom" (Appendix Figure A1).[7] 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.

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[5] Female scientists reported a 5% larger decline in research time, compared with men, and cientists with children below the age 6 experienced a 17% larger decline in research time compared with scientists with older children.

[6] Examining registry data for Denmark between 1980 and 2013, Klevens, Landais, and Soogard (2019) show that children reduced the earnings of women by 20% relative to men. Analyses of survey data on MBA graduates (Bertrand, Goldin, Katz 2010, p. 241) find that nearly half of the earnings deficit for women can be explained by reduced weekly hours and no-work spells for women with children.

[7] There are many competing explanations for the causes of the baby boom. Doepke, Hazan, and Moaz (2015) show that some of the increase in births after the war may have been a consequence of the increase in demand for female labor during World War II. When women of the war generation stayed in the labor force after the war, they made it harder for younger women (without work experience) to get jobs, encouraging them to exit the labor market and have children. There is, however, an active debate on whether the women who entered the labor force during the war stayed after the war (e.g., Goldin 1991 and Rose 2018).

A rising industrial demand for scientists made it possible for young scientists and graduate students "to live, and to have wives and children like normal people." (Merle Tuve, cited in Kevles 1995, p. 370.) "Government laboratories, from the established Bureau of Standards to the new Oak Ridge, Argonne, and Los Alamos, could not get enough physicists. The greater the nonacademic demand, the greater the demand for professors to teach the discipline" (Kevles 1995, p.370). In 1956, when the American Physical Society held its meeting in New York City, recruiters "mobbed" the meetings "enticing and pirating candidates for industrial, governmental, and academic positions" (Kevles 1995, p.370).

During the baby boom, women "bore and raised children in their early twenties," creating a "collapsed period of intensive child rearing" and a "relative freedom from such demands that followed when they reached their late thirties and early forties" (Weiss 2020, p.8). Couples also had children more quickly after they were married and spaced their children closely together (Weiss 2020, p. 4).

1.2. Social Norms Place the Burden of Childcare Squarely on Women

Socially, women were expected to focus their attention on the home, and many historians have attributed the underrepresentation of women in science to a "preference" for housework and children over pursuing a career. In his history of American physics, Daniel J. Kevles (1995, 1st ed. 1971, p.371), for example, explains that:

> 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.

Institutional barriers further discouraged the participation of women in both academia and industry. Prohibitions against the employment of married women in teaching and clerical work, termed "marriage" bars," which had arisen between the late 1800s and the early 1900s, remained in place until the 1950s. At their height, marriage bars affected 87% of school districts and about 50% of office workers (Goldin 1990, pp.160-61).

Academia was affected by similar restrictions, obstructing the entry of women: "In the academic world, where some graduate departments still refused to admit female applicants, women were still mainly consigned either to the women's colleges, or at other institutions, to second-class posts on the research, as opposed to the professorial staff" (Kevles 1995, p.371).

II. BIOGRAPHIES LINKED WITH PATENTS AND PUBLICATIONS

Our main data consist of detailed biographical information on 82,094 American scientists, matched with their US patents between 1910 and 1970. Data include each scientists' gender, place of birth (which we use to identify foreign-born scientists), date of birth (which we exploit to create a high-quality match between scientists and their patents), as well as records on naturalizations, education, and employment (allowing us to investigate changes in the arrival of foreign-born scientists in the United States).

2.1. Biographies of 82,094 American Scientists

Biographical data are drawn from the *American Men of Science* (MoS 1956). 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.[8] 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 *American Men of Science* include both male and female scientists in Canada and the United States.

Detailed biographical data for 82,094 American scientists in 1956 allow us to examine US science at the height of the baby boom.[9] Beyond the Physical Sciences (volume 1), and the Biological Sciences (volume 2), the 1956 edition also includes the Social & Behavioral Sciences (volume III, 15,493 scientists). We use this disciplinary division to improve the patent matching.

Data in the MoS (1956) were subject to comprehensive input and review from "scientific societies, universities, colleges, and industrial laboratories." Jacques Cattell thanks them 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

[8] Like many of his contemporaries, Cattell was intrigued by eugenics. Cattell's own brand of eugenics motivated him to offer his children $1,000 each for marrying the offspring of another professor.

[9] This count excludes 6,352 duplicate mentions of scientists who appear in more than one of the three volumes of the MoS (1956) as well as 2,015 scientists whose entry consists only of a reference to another MOS edition and 534 scientists whose entry consists only of a reference to Cattell's *Directory of American Scholars* (1957).

Science and the National Academy of Science National Research Council "which acted in an advisory capacity" (Cattell 1956, Editor's Preface).

2.1.1. Female Scientists

We assign gender based on the share of women with the same name in US Social Security Administration Records (SSA) between 1880 and 2011.[10] Among 82,094 American scientists, 4,220 are women (5.1%), 66,560 are men (81.1%), and 11,314 have unknown gender (13.8%). In the main specifications we compare outcomes for female scientists with outcomes for men and exclude scientists of unknown gender. Robustness checks repeat the main specifications assigning the "unknown" to be women.

To check the SSA assignment, we compare it with four alternatives: 1) manual assignment based on the scientists' name, 2) attendance at a women's college, 3) the share people with the same name who are women in the census of 1940, and 4) R's *gender* package (Appendix B). In addition, we hand-checked a random sample of scientists by comparing their gender with publicly available sources. Unsurprisingly, the gender detector algorithm performs poorly for Asian first names. The chemist Dr. Miyoshi Ikawa (b.Venice, Calif. Feb 24, 1919, married 1950, 1 child), is a woman according to the SSA records, yet images in Ikawa's funeral records (matched through name and the exact birth date) indicate that Ikawa was male. To address this issue, we hand-checked Asian names in the MoS. Due to discriminatory immigration policies and hiring, such names are extremely rare in our data.

2.1.2. Date and Place of Birth

Information on the precise date of birth for each scientist allows us to assign scientists to birth cohorts and examine changes in career paths, marriage decisions, and childbirth over time. Birth years also make it possible to count the number of scientists who, in any given year, were in a plausible age (between 18 and 65 years) to work as scientists in the United States. We use the number of scientists in this age range to estimate the number of scientists who were active in the United States in a given year, and to calculate productivity measures based on patents per

[10] Gender-detector 0.1.0 (https://pypi.org/project/gender-detector/: accessed June 25 2020). Jeremy B. Merrill, who created the algorithm, describes it as "A minimum estimated value: a best guess of the ratio of genders of people with a given name. A minimum lower confidence bound: only 2.5 times out of a hundred (by default) with the actual proportion of genders of people with this name fall below this bound." We set statistical significance to 95.

scientists and year. In addition, we use the scientists' ages to refine the matching of patents with scientists (by using patents by extremely young or old people as a proxy for false positives). 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%).[11]

2.1.3. Marriage and Children

A key advantage of the MoS is that it records whether scientists have children. For example, the entry for Dr. Giuliana C(avaglieri) Tesoro tells us that she was married in 1943 and had two children, "m. 43; c. 2" in her entry below:

> 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.

By contrast, Gertrude Belle Elion (Nobel Medicine 1988) remained unmarried after her fiancé died of endocarditis in 1941, and her entry shows no marriage and no children:

> ELION, GERTRUDE B(ELLE), Wellcome Research Laboratories, Tuckahoe 7, N.Y. BIOLOGICAL AND ORGANIC CHEMISTRY. New York, N.Y. Jan. 23, 18. A.B. Hunter Col. 37; M.S. N.Y. Univ, 41. Lab. Asst. biochem. sch. nursing, N.Y. Hosp. 37; research asst. org. chem, Denver Chem. Co, 38-39; teacher chem. and physics, New York, N.Y. 41-42; analyst food chem, Quaker Maid Co. 42-43; research chemist org. chem, Johnson and Johnson, 43-44; SR. BIOCHEMIST, WELLCOME RESEARCH LABS, 44- Chem. Soc; Soc. Biol. Chem; N.Y. Acad. Chemistry of Purines, Pyrimidines and Pteridines; bacterial metabolism; metabolism of radioactive purines in bacteria and animals.

Data on scientists' children is particularly valuable because it is impossible to get such data for the baby boom years from the US census data. Individual-level census records are only available until 1940, while the MoS includes children born by 1955.

2.1.4. University Education

Data on university degrees are available for 4,020 women (99.7% of 4,032 women with gender and birth years) and 65,821 male scientists (99.4% of 66,198 men with gender and birth

[11] In addition to birth dates, the MoS (1956) also includes the place of birth for 99.5% of all 82,094 American scientists in 1956. These data allow us to separate US-born women and men in science from immigrants.

years).[12] The MoS (1956) reports undergraduate degrees for 3,755 of 4,032 female scientists (93.1%) and 61,005 of 66,198 male scientists (92.2%). PhD degrees and graduation years are recorded for 3,254 of 4,032 female scientists (80.7%) and 46,913 of 66,198 male scientists (70.9%).[13]

We use these data to inform two types of analysis. First, we investigate differences in the rates at which women and men transitioned from college to graduate school and in the transition from PhD to university jobs (described in more detail below). Second, we examine differences in the rate at which women and men with and without children entered US science.

2.1.5. Job Titles and Employment Histories

Information on job titles and dates of employment allow us to identify academic scientists and to examine differences in the rates of promotion to tenure. We define as academic scientists any scientist who chose to work in academia as some point in their career, and held academic job titles like assistant professor, associate professor, professor, research fellow, instructor, visiting professor, clinical professor, adjunct professor, professor emeritus, or dean. For example, Alice Dickinson Awtrey is an *academic* scientist because she worked as an assistant professor:

> AWTREY, PROF. ALICE D(ICKINSON), Dept. of Chemistry, Iowa State College, Ames, Iowa. INORGANIC AND PHYSICAL CHEMISTRY. New York, N.Y, Nov. 14, 26. A.B, Radcliffe Col, 47; Ph.D.(chem), California, 50. Instr. Chem, California, 50-51; fellow, Cornell, 51-52; ASST. PROF. CHEM, IOWA STATE COL, 52- A.A; Chem. Soc. Inorganic equilibria and kinetics in aqueous solutions.

By comparison, Giuliana Tesoro, worked exclusively in industry as a "Research chemist, Calco Chem. Co. N.J., 43-44; ONYX OIL & CHEM. CO, 44-46, HEAD ORG. SYNTHESIS DEPT. 46," and for Tesoro the variable *academic* scientist equals zero. Three quarters, 52,946 of all 70,230 scientists in 1956, are *academics;* 3,537 (87.7%) of 4,032 female scientists and 49,409 (74.6%) of 66,198 male scientists are *academics*. For scientists who were promoted to tenure, we

[12] Undergraduate degrees include Bachelors of Science, Arts, Chemistry, and Education.
[13] 3,265 of 4,032 female scientists (81.0%) and 47,715 of 66,198 male scientists (72.1%) hold other advanced degrees, such as master's degrees or M.D.s.

calculate *time to tenure* as the years between their first year as an assistant professor position and their first year as an associate or full professor.

2.1.6. Research Topics and Fields

A unique feature of the MoS (1921 and 1956) is that scientists report both their research topics and disciplines. Attie Betts, for example, works in "electrical engineering" and researches "Supervisory control by UHF link; telemetering by UHF link; ultra-sonic treatment of dielectric materials; reflection from conducting materials; unconventional sources of electrical power." Giuliana Tesoro works in "organic chemistry" and researches the "Synthesis of pharmaceuticals, textile chemicals, germicides and insecticides; synthesis and rearrangement of glycols in the hydrogenated naphthalene series." Disciplines are known for 99.97% of all 82,094 scientists in 1956. Disciplines range from the extremely broad ("chemistry" or "physics") to specific ("crystallographic chemistry" and "mathematical electrophysics").

Implementing a methodological approach from Moser and San (2020), we apply *k*-means clustering to assign each scientist to a unique research field, using the words that describe their research topics and disciplines. These assignments allow us to control for differences in the propensity to patent, publish or cite existing research across fields across research fields (e.g., Moser 2012). Information on fields also allow us to examine whether differences in output and career outcomes might be driven by the occupational or field choices of women.

2.2. Matching Scientists with their Patents, 1930-1970

To measure changes in the productivity of scientists, we match scientists with their US patents, implementing an improved matching process that takes into account the age, full name, and discipline of each scientist (described in more detail in the Data Appendix A). Data include 130,902 successful patent applications by American scientists, with 665 patents by 4,032 female scientists and 130,237 patents by 66,198 male scientists.[14]

In our analyses of patenting, we focus on the physical sciences, or STEM fields, which have the highest match quality between scientists and their patents. Patent data in the physical

[14] At the time, patents were more likely to be awarded to single inventors compared with today. The median patent in our data has a single inventor with an average of 1.24 MoS inventors per patent and a standard deviation of 0.51. Appendix Table A3 presents robustness checks that control for the number of inventors on a patent by dividing each patent by the total number of MoS inventors.

sciences cover 122,935 patents by 35,368 scientists, including 598 patents by 1,172 women and 122,337 patents by 34,196 male scientists. 93.9% of all matched patents in our data are in STEM. Controlling for middle names and excluding the top quintile of common names, the rate of false positives for the physical sciences is just 4.2%. By comparison, 32.8% for the biological sciences and 67.9% for the social sciences are false positives, largely because most innovations in the biological and physical sciences were not patentable.[15] We therefore exclude the biological and social sciences in the main specifications and include them in robustness checks for patents and publications.

2.3. Matching Scientists with their Publications

To match scientists with their publications we search for each scientist's name in the list of authors in the Microsoft Academic Graph (MAG) database.[16] MAG is updated each week; we use the version of the data 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 leads female scientists, with 240 publications.

The average publication has 2.27 authors (with a median of 2 and standard deviation of 2.25). To control for such variation, we divide publications by the number of authors when we count publications per author and estimate robustness checks counting each publication fully per author (even if there are more than one author). Field fixed effects control for variation in the size of author teams across fields.

[15] For a detailed description of the matching process see Moser and San (2020).
[16] Moser and Parsa (2020) use these data to examine the effects of political persecution during the McCarthy period on American scientists who appeared as communists on McCarthy's lists of "reducators."

A key benefit of publications as an output measure is that we can control for differences in quality by comparing the number of future works that cite each publication.[17] Our data include 141,952,592 citations to 754,581 publications by 70,189 scientists between the ages of 18 and 65 (188.1 per publication) and 144,933,096 citations to 790,180 publications by 70,230 scientists between the ages of 18 and 80 (183.4 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 work with George E. Palade, a 1974 Nobel laureate.

An advantage of the MAG data when compared to the MoS is that it records the number of authors per publication. By dividing the publications and their citations by their respective numbers of authors, we obtain an author-weighted publication counts for each scientist in the MoS. This allows us to prevent the multiple counting of publications and their citations and better estimate the individual productivity of each scientist. We use this author-weighted measure in the main analyses of our paper.

Using this new measure for publications, our data include 469,380.2 journal publications by 70,189 scientists between the ages of 18 and 65 (6.7 per scientist) and 493,249.7 publications by 70,230 scientists between the ages of 18 and 80 (7.0 per scientist). For author-weighted citations, our data include 76,979,858.3 citations to 469,380.2 journal publications by 70,189 scientists between the ages of 18 and 65 (164.0 per publication) and 78,743,655.0 citations to 493,249.7 publications by 70,230 scientists between the ages of 18 and 80 (159.6 per publication).

2.4. Matching Scientists with Census Records

For supplementary analyses, we match scientists with the 1940 US Census microdata to identify the birth year of each child and to glean information on the scientist’s family. First, we create a simple matching algorithm to identify census records for individuals who 1) are born in the same state as the scientist 2) are no more than three years younger or older than the scientist

[17] Patent citations – references to prior patents in future patents – are less suitable as a measure of quality for the current analysis because they are not systematically recorded in patent documents until 1947.

and 3) have a similar first and last name, defining similarities as a Jaro-Winkler distance of 0.2.[18] Since many women change their last names upon marriage, they are more difficult to match algorithmically than men, and we supplement the algorithm with manual matching. The combination of algorithm with manual matching yields 227 unique matches among 892 scientists who are mothers (37.8%).[19] Among them, 191 report children living in the same household at the time of the census count in 1940; another 2 report children living elsewhere.

We use matched scientist-census records to compare changes in productivity for mothers and fathers of the same household. Information on grandmothers and servants allows us to explore whether access to childcare helps to mitigate child penalties in science.

III. PRODUCTIVITY DIFFERENCES ACROSS DEMOGRAPHIC GROUPS

In this section, we analyze scientist-level data on changes in patenting across the life cycle and over time to investigate how children influence productivity. First, we estimate age-specific changes in output separately for each demographic group (mothers, fathers, women and men without children). Second, we compare levels of inventive output across demographic groups. Third, we estimate event studies of changes in inventive output after marriage to investigate the causal effects of children on productivity.

3.1. Changes in Inventive Output across the Life Cycle

How do children affect the *timing* of productivity? To investigate this question, we first examine changes in inventive output across the life cycle of scientists. Raw counts of patents per age show that the life cycle productivity of mothers is very different from that of other demographic groups (Appendix Figure A2). Mothers become more productive in their late 30s and early 40s, while other scientists peak in their mid 30s. Mothers generate 7.0 patents per 100 scientists and year at age 42, a 3-fold increase compared with their own productivity at age 27, the median age of marriage for female scientists. Mothers continue to be highly productive in their 40s, with 4.0 patents per year between 40 and 44 and 3.3 per year between 45 and 50. By

[18] The Jaro-Winkler distance (Winkler 2006) is a string measure for the edit distance between two sequences (here, letters in the scientist's first and last name). The lower the Jaro-Winkler distance between two strings, the more similar the strings. A distance of 0 represents an exact match, and a distance of 1 means implies no similarity.
[19] 451 of 892 mothers had not yet married in 1940; 352 of them were below 27, the median age at marriage for female scientists.

comparison, fathers peak at 37 (with 18.4 patents per 100 scientists and year, Appendix Figure A2, Panel A), and experience a continuous decline in productivity after 40. Mothers also become more productive relative to other women later in life (Panel C). Notably, there are no significant differences in life cycle patterns of productivity between women and men without children (Panel B), and fathers are again slightly more productive than other men (Panel D).

To investigate life-cycle productivity more systematically – controlling for unobservable forces, such as gender discrimination, that may depress the productivity of women – we investigate changes in patenting across the life cycle of scientists *separately within demographic groups*. Specifically, we estimate OLS models

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

where y_{ia}^{d} is the number of US patents (or publications) per 100 scientists i of demographic *d* in age a. Inventive output is measured by patents in year *t* by scientists of age *a* in calendar year *t* of the patent application; the excluded age is 20. The coefficient β_a^d is a vector of age-varying estimates of inventions (publications) created at age *a* by scientists of demographic *d* compared with scientists in the same demographic at age 20. δ_t are patent application year fixed effects to capture variation in invention intensity over time (e.g., as a result of variation in research funding); π_y are fixed effects for birth years *y* to control for variation in productivity across cohorts (e.g., as a result of differences in exposure to research funding). Field year fixed effects μ_f control for variation in the propensity to patent (or publish) across fields *f.*

For mothers, age-specific estimates of invention productivity increased until the median age of marriage, declined afterwards, and increased again after age 35 (Figure 1). Between the ages of 20 and 27 (the median age of marriage for women), inventions per year by scientists who ultimately had children increases from zero at age 20 to an additional 4.0 patents per year (Figure 1, with p-value=0.205). After 27, mothers become significantly less productive through their late twenties and early thirties. Mothers' patenting declines to 2.7 additional patents at 30 (p=0.135), 4.4 at 32 (p=0.048), 3.4 at 34 (p=0.045), and 2.0 at 35 (p=0.253). Notably, mothers' productivity makes a strong recovery after age 35, and continues to increase to a peak of 6.5 additional patents at age 42 (p=0.282).

Age-varying estimates for other demographic groups show that this late productivity boost is unique to mothers. Estimates of β_a^{ow} for other women indicate their productivity peaks with 3.8 additional patents at age 30 (p=0.110) and then declines to 2.5 at 35 (p=0.016), 2.7 at 40 (p=0.017), and 3.0 at age 45 (p=0.019). Estimates of β_a^f for fathers show that their productivity peaks in their late 30s and declines continuously afterwards (Figure 1). Invention by fathers increases steadily to a peak of 16.5 additional patents at age 35 (p=0.000). After 35, patenting declines slowly to 15.8 additional patents at 40 (p=0.000), 10.6 additional patents at age 45 (p=0.000), 7.5 at age 50 (p=0.000), 4.2 at age 55 (p=0.000), 2.0 at age 60 (p=0.018), and 1.1 fewer patents at age 65 (p=0.257). Estimates of β_a^{om} for male scientists w*ithout* children show a similar pattern over time, with a peak in patenting at age 38 (14.0 additional patents compared with males without children when they were 20 years old, p=0.000, Figure 1).

3.2. Differences in Inventive Output Across Demographic Groups

Summary statistics on patents and publications indicate that mothers were at least as productive as other women, but much less productive than fathers and other men. Per 100 scientists, mothers produced 65 patents, substantially more compared with 47 patents by other women, but also much less than 382 patents created by fathers (Table 1). Some of this pronounced gender difference in patenting may have been due to discrimination. For modern data, an analysis of 2.7 million recent US patent applications suggests that female inventors face less favorable outcomes in examinations and patent disputes to this day (Jensen, Balázs and Sorenson 2018). In the analyses below, we address this issue by comparing changes in patenting *within demographic groups*.

To examine differences in productivity more systematically, with controls for differences in productivity over time, across birth years, and across fields, we estimate OLS models:

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

where the dependent variable y_{it} counts US patents per 100 scientists i in year *t*. The variable $Parent_i$ indicates scientists who were parents in 1956, $Female_i$ indicates scientists who are women, and $Female * Parent_i$ indicates scientists who are mothers; δ_t are year fixed effects (to control for changes in patenting and publications over time, for instance, as a result of changes in research funding). A vector π_b of birth year fixed effects controls for variation in patenting across cohorts (e.g., as a result of changes in access to education or research opportunities during World War II). μ_f are field fixed effects to control for variation in the propensity to patent across fields f (e.g., Moser 2012). For example, scientists may patent less in theoretical fields, like mathematical analysis compared with applied fields, like chemical engineering. Field fixed effects control for these differences.

OLS estimates show that mothers patent slightly 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 -5.870 fewer patents per 100 scientists and year, Table 2, column 1, significant at 1%) compared with a pre-baby boom mean of 8.811 patents per 100 scientist and year. Mothers patented 77% *less* than fathers (-5.870-0.912 in Table 2, column 1 divided by the mean), but 9% more than other women (1.772-0.912 relative to the mean). All results are robust to controlling for age fixed effects (column 2, replacing cohort fixed effects), including older scientists up to age 80 (column 3).

Extending the analysis to all fields, including the biological and social sciences, confirms these results. Across all fields, gender differences in output are less pronounced: Relative to the pre-baby boom mean of 4.6 patents per year, an estimate of -2.3 for female indicates that women patent "just" 52% less compared with 67% less in STEM. Yet, estimates for parents across all fields are nearly identical to STEM: Mothers patent 71% less compared with fathers and 7% more than women without children. Arguably, patents are a noisy output measure for the biological and social sciences (Moser and San 2020), and to address this issue, we repeat these analyses with publications below.

Mothers produced more invention in STEM and other disciplines, possibly because, to survive in science, they had to be exceptionally productive. We examine selection more thoroughly below, in section VI. Notably, fathers were also consistently more productive than other men. On average fathers patented 382 inventions per 100 scientists, 35.0% more than other men (283 patented inventions), and they published 1,191 papers, 9% more compared with 1,090 papers by other men. These findings suggest that differences in productivity may be a driving force behind higher earnings for fathers, which have been documented in previous work (e.g., Goldin 1990, Bertrand et al 2010).[20]

[20] While earnings of female MBAs decline sharply three to four years after the birth of their first child (Bertrand et al. 2010, p. 248-9), MBA men see their earnings increase five years or more after the birth, and their labor supply is virtually unaffected. Goldin (1990, p. 102) shows that married men in manufacturing have earned 17% more historically compared with single men, while there was no difference for married and single women. This marriage premium for men has remained stable since the 1890s (Goldin 1990, p. 91). Using data from the American Community Survey for 2013-17, Martell and Nash (2020) document a substantial marriage premium for married gay men and women and find that the marriage premium is double for the higher-earning spouse. This suggests that marriage encourages specialization in same-sex families similarly to different-sex households.

Intensity estimates for the *number* of children (Appendix Table A1) suggest that the productivity of mothers was hit most by the first child, while fathers became more productive with each child. Fathers also produced more patents than other men, with 1.669 additional patents per 100 scientist and year (Table 2, column 1, significant at 1%), equivalent to an 18.9% increase compared with the mean. For the late 20th century, Korenman and Neumark (1987) show that the marriage premium increases with the duration of marriage, which they attribute to greater labor market efforts of men with dependents. A similar mechanism may be at play for fathers who are scientists, encouraging fathers with more children to create more patents.

3.3. Event Studies of Changes in Output after Marriage

Changes in productivity across the life cycle suggest that mothers are less productive in their 20s to early 30s, at a time when many of them are pregnant or caring of young children. We now investigate this change in productivity may be a causal effect of children. An ideal experiment would randomly assign children to scientists. Since this is impossible, we estimate event studies for marriage, as a proxy for the birth of the first child. During the baby boom, parents had their first child soon after they married (Weiss 2020, p.4). We exploit this historical fact to estimate separate regressions of changes in productivity after the year of marriage for mothers, fathers, and other married women and men without children.

Empirically, the event study approach takes advantage of sharp changes in productivity after marriage. While a scientist's choice to have children may not have been exogenous, the event of marriage (and with it the birth of the first child) creates a sharp change in productivity. This sharp change in productivity after marriage is arguably orthogonal to unobserved determinants of productivity that evolve more smoothly over time. For example, some may argue that people have children because they are less serious about work, which also makes them less productive. The effects of such preferences would evolve smoothly over time, while any changes in output due to children happen more abruptly.

Another benefit of the event study approach is that it allows us to trace out the long-run trajectory of changes in productivity after marriage. Taking full advantage of the richness of the historical data, this analysis allows to investigate changes for more than years after marriage, covering the scientist's entire career. This approach is particularly important for capturing changes in the timing of productivity for mothers, whose peak productivity might be delayed. Event study models estimate OLS equations

$$y_{is}^{d} = \beta_{s}^{d} EventTime_{i} + \delta_{t} + \alpha_{a} + \mu_{f} + \epsilon_{it} \quad (3)$$

where we index the event time *s* relative to the year of marriage and y_{is}^{d} is the number of US patents per scientist i of demographic d (mothers, fathers, and other married women and men) in event year s. The coefficient β_{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 β_{s}^{d} estimate the impact of children relative to the last year before marriage. Age fixed effects α_{a} control for variation in output across the life cycle of a scientist. Calendar year dummies and other variables are defined as above.[21]

Event studies of patenting after marriage confirm that mothers are less productive for the first 15 years of their marriage but then experience a large boost in inventive output (Figure 2). In 7 of the first 15 years after marriage, estimates of β_{y}^{m}, indicating a persistent decline in the productivity. After 15 years, however, mothers' productivity recovers and increases to 6.8 additional patents 20 years after marriage (p=0.295), 6.9 patents 22 years after marriage (p=0.141), 6.2 additional patents 25 years after marriage (p=0.058), and 5.0 additional patents 30 years after marriage (p=0.011). Notably, these estimates exceed estimated productivity increases for all other demographic groups.

Notably, productivity increases only for mothers and not for any other demographic group. In fact, event study estimates of β_{y}^{f} show that fathers (*parents* who are not *female*) become significantly more productive in the first 10 years of marriage (Figure 2). Compared with their own output one year before marriage, fathers' productivity increases to 4.0 additional patents 5 years after marriage (p=0.000) and 5.6 additional patents after 9 years (p=0.000). Fathers' productivity begins to decline after the first decade of marriage with 3.5 additional patents after 15 years (p=0.000), 1.1 additional patents after 20 years (p=0.154), and 0.52 fewer patents 30 years after marriage (p=0.531). Event-study estimates for other men (β_{y}^{om}) follow a similar pattern, increasing 5.3 additional patents after 9 years (p=0.006) and declining

[21] Since there is variation in event time *y* driven by the year of marriage (conditional on age and year) these specifications can 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*.

afterwards. Estimates for other women (β_y^{ow}) remain close to estimates for mothers for the first 15 years, albeit with higher productivity in the early years of marriage. While mothers become more productive after the first 15 years of marriage, output by other women declines, similar to the output of male scientists.

3.4. Why Are Mothers More Productive Late in Life and Late in Marriage?

Why do mothers patent so much in their late 30s and early 40s, as well as 15 years into their marriage, after the productivity of other scientists has started to decline? The most straightforward explanation is that childcare becomes less labor-intensive as children grow up, leaving mothers more time to do research. 15 years after marriage, the youngest child in most baby boom families would have been older than 12, an age that generally requires less care than the average 3- or 5-year old. In 2019, mothers spent 2.8 hours per day caring for children under age 6, compared with just 1.2 hours per day in households whose youngest child was 6 to 12 years old (BLS 2020).[22]

An alternative explanation may be that the late-in-life increase in scientific productivity reflects a pent-up supply of research ideas. Speaking against this hypothesis, non-work spells have been found to greatly damage a person's career, especially when they occur at a young age (e.g., Davis and von Wachter 2011; Oreopoulus, von Wachter, and Heisz 2012; Guvenen et al 2017; Jarosch 2015). Kuka and Shenhav (2020) show that mothers who were differentially affected by the 1993 reform of the Earned Income Tax Credit, and therefore faced an increased incentive to return to work, accrued 0.5-0.6 additional years of work experience and had 4.2% higher earnings. Research on skill obsolescence implies that non-work spells may be particularly costly for young scientists, especially in fields such as science, where the frontier of research moves quickly. McDowell (1982) documents exceptional decay rates of knowledge for physics and chemistry. MacDonald and Weisbach (2004) develop a "has-been model" which shows that skill obsolescence among older workers increases with the pace of technological change.

[22] Fathers, by comparison, spent 1.42 and 0.69 hours per day with younger and older children, respectively.

IV. Effects of Children on Publications and Tenure

Our analyses of patents indicate that, while children reduce the productivity of mother early in life and early in marriage, mothers who survive in science show remarkable productivity gains after age 35 and after the first 15 years of marriage. These unique life cycle patterns of productivity may disadvantage mothers when it comes to tenure. We investigate this issue by comparing life cycle patterns of publications and promotions for mothers and other scientists.

4.1. Changes in Publishing Productivity Across the Life Cycle

Age-specific estimates for publications confirm the unique life-cycle pattern of mothers' productivity. Mothers publish more early in life but reduce their output after the age of 27, the median age of marriage for female scientists in the MoS (1956). Importantly, their productivity recovers after age 35 and continues to increase until their early 40s (Figure 3).

Age-specific estimates of equation (1) for publications show that mothers' publications increase up to age 27, the median age at marriage for female scientists. At age 27, mothers produce 16.3 additional publications per year compared with themselves at age 20 (p=0.015). After age 27, mothers fall behind until their mid 30s; at age 35 mothers produce 13.1 additional publications (p=0.000). Confirming results for patents, mothers begin to recover and reach peak productivity at age 42, producing 20.3 additional publications compared with themselves at age 20 (p=0.000), long after the productivity of other scientists has started to decline.

4.2. Differences in Publishing Productivity Across Demographic Groups

Confirming results for patents, mothers published slightly more on average than other women (with 5.39 and 5.06 publications per scientist, respectively) but significantly less than fathers (with 7.23 publications). Notably though, the *quality* of publications by mothers is extremely high and increasing after age 35. The average publication by a mother in STEM receives 41.99 citations, higher compared with just 23.10 citations per publication by other women, but still lower than 123.99 citations per publication by fathers (Table 1).

To evaluate these differences more systematically (with controls for differences in the intensity of publishing over time, across birth cohorts, and across fields) we re-estimate equation (2) for publications and citations. OLS estimates confirm pronounced gender differences in productivity: Mothers publish roughly as much as other women but much less than fathers or other men. On average, female scientists publish 75% fewer papers compared with men (based on an estimate of -8.355 for *Female* in Table 3, column 1, significant at 1%, relative to a pre-baby boom mean of 11.189 publications per 100 scientist and year). Confirming findings based on patents, mothers publish 85% less than fathers (with an estimate of -8.335 for *Female* and -1.108 for *Female*Parent* in Table 3, column 1). All results are robust to controlling for age fixed effects (column 2) and to including older scientists (column 3).

Citations data suggest that publications by mothers were substantially more influential than publications by other women. On average, papers by female scientists receive 42.7% fewer citations than papers by men (based on an estimate of -9.077 for *Female* in Table 3, column 7, significant at 1%, relative to 21.275 citations per publication before the baby boom). Publications by mothers, however, receive 17% more citations compared with other women (with estimates of -9.077 for *Female*, -9.248 for *Female*Parent*, and 14.091 for *Parent*, all significant at 1%, Table 3, column 6).

Why do mothers *publish* roughly the same as other women, while they patent slightly (8%) more? Differences in productivity for patents and publications could reflect differences in the intensity of selection or in productivity: Mothers may be less able to accommodate long hours of laboratory work required to patent than other scientists, 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.

Publication data also confirm that, compared with STEM, gender differences were less severe in the biological and social sciences. Across all disciplines, female scientists published 63% fewer papers than men (with an estimate of -9.959 for *Female* Table 3, column 6) compared with a pre-baby boom mean of 15.832 publications per 100 scientist and year. Mothers also published 65% less than fathers (with an estimate of -9.959 for *Female* and -0.353 for *Female*Parent* in Table 3, column 6). Compared with other women, mothers publish slightly more across all disciplines (with an estimate of -0.353 for *Female*Parent* and 0.829 for *Parent* Table 3, column 6). Thus, publication data indicate that gender differences in output were larger in STEM than in other disciplines, and that, across all disciplines, mothers who survived in science were more productive than other women.

4.2. Effects of Children on Tenure

How do differences in the timing of output influence promotions? Career disruptions have been shown to damage future wages and job security, especially if they happen early in a person's career (e.g., Oreopoulus, von Wachter, and Heisz 2012; Jarosch 2015). Examining data for academic economists Dowell et al. (1999) find that women are less likely to be promoted than men, even though promotion opportunities for women from associate to full professors have improved. Our analyses complement this research by comparing the rate and speed of promotions for mothers and other scientists. In addition, we examine differences in output before and after tenure.

Among scientists who held an academic job at least once, just 2% of mothers achieved tenure (Table 4), 21% less than fathers (whose tenure rates were 48%, Table 4). Notably, the tenure penalty of women is felt almost entirely by mothers, while tenure rates for other women are almost identical to those of men: 46% of other women without children get tenure.[23] While mothers are heavily penalized for parenting, fathers are slightly more likely to achieve tenure than other men. 48% of fathers get tenure, compared with 47% of other men.

Data on the speed of promotions show that mothers fall behind other scientists five years after they become assistant professors (Figure 4). In the first five years after the start years of their first assistant professor job, the cumulative share of mothers reaching the rank of associate or full professor tracks that of other scientists. After five years, however, the tenure rate of mothers flattens while other scientists continue to advance.[24]

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

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

[23] Tenure rates for other married women (without children) are also low. Just 29.2 percent of 636 married women without children achieve tenure, compared with 50.6 percent of women who did not marry. Low tenure rate for married women without children may reflect statistical discrimination against married women, if employers expect them to have kids. Alternatively, low tenure rates for married women may reflect a disadvantage if women have to move with their husbands. 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 is likely to benefit male scientists, it may hurt their wives who have to move along.

[24] On average, 38% of mothers who were assistant professors earned tenure, compared with just 27% of mothers who held any academic position, including academic jobs off the tenure track (Table 4). This difference arises because just 36% of mothers get tenure track assistant professor jobs, compared with 45% of fathers and other women, respectively (Table 4).

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

Estimates of β_y^m for mothers (Figure 5) indicate that the productivity penalty of motherhood created major long-run damage on tenure rates of mothers. 15 years after marriage, mothers were 10.3% less likely to be tenured (p=0.025), compared with themselves one year before marriage. With each additional year of marriage, tenure rates for mothers continue to decline, even as their productivity increased. After 20 years of marriage, mothers were 10.3% less likely to hold a tenured position (p=0.040).

At the same time, tenure probabilities of fathers increase after marriage. Estimates of β_y^f show that, 15 years after marriage, fathers are 16.7% more likely to get tenure compared with themselves just before marriage (p=0.000). Estimates increase to 19.7% after 20 years (p=0.000), 25.0% after 25 years (p=0.000), and 30.1% after 30 years (p=0.000). Event-study estimates for other married men (β_y^{om}) follow a similar pattern over time, although at lower levels. Estimates for β_y^{ow} also show similar patterns; 15 years after marriage, other married women are 14.2% more likely to receive tenure compared with themselves just before marriage (p=0.001). Estimates increase to 17.3% after 20 years (p=0.000), 20.4% after 25 years (p=0.000), and 30.4% after 30 years (p=0.000).

4.3. Changes in Publications before and after Tenure

Did tenure affect the publishing productivity of scientists? And did scientists' output change differentially after tenure across demographic groups? To investigate these questions, we separate first estimate age varying effects in equation (1) separately for scientists without and with tenure, across demographic groups.

Age-varying estimates for scientists without tenure show that even mothers without tenure became more productive after age 35. Their publications plateaued in their early 30s but start to recover after age 35. Mothers without tenure sustained high levels of productivity through their 50s (Appendix Figure A5, Panel A). By comparison, publications by other women decline in their 40s, and publications by fathers and other men peak around age 35.

Mothers with tenure experience a large boost in productivity throughout their 40s (Appendix Figure A5, Panel B), while the productivity patterns of other scientists evolve more smoothly. Publications of other women follow a similar trend as that of men. While mothers have a later peak in productivity in their early 40s, other women peak at age 36, very similar compared to a peak around age 37 for fathers and other men.

Was this burst in productivity for tenured mothers due to increased productivity leading up to tenure? And more generally how did scientists who got tenure change their publication output relative to the year of marriage? To examine this question, we re-estimate event studies in equation (3) comparing changes in publications relative to the year of tenure. Importantly, these estimates cannot measure a causal effect of tenure on publications because tenure is a result of publications. Instead, these estimates only allow us to observe the productivity of scientists in different demographic groups after tenure.

Event study estimates for publications show that mothers become more productive after tenure, reaching peak productivity 5 to 16 years after tenure. By comparison, the productivity of all other scientists stays either flat or declines after tenure (Figure 6). Male scientists with and without children publish more until the year of tenure; after tenure their productivity stays flat. Other women without children experience a decline in productivity after tenure. Only scientists who are mothers become more productive after tenure.

V. SELECTION

We have found that, while mothers are less productive compared with both fathers and childless women in their 20s and early 30s, they experience a large productivity boost after age 35. Event studies further show that mothers are less productive in the first 15 years after marriage but recover and improve while other scientists decline. Could these changes be a result of selection? To answer this question, we investigate selection into investments in education, into tenure track jobs, into marriage and parenting, into research fields, and, finally, into survival in academic science.

5.1. Female Scientists Were More Likely to Have PhDs

Almost any model of human capital investment implies that women, who expect to 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). “The return to investments in firm-specific human capital and to labor market search is higher for persons who work full-time and who do not expect to leave their firms to engage in non-market work or to accommodate a spouse who is transferred to another part of the country” (Altonji and Blank 1999, p. 3167). Moreover, if women expect discrimination, they may be less (or more) likely to invest in human capital, such as a PhD, required to advance from assistant to associate professor. Coate and Loury (1993) for example, show theoretically that discrimination can influence human capital decisions both before and after a person enters the labor market.[25]

Women also have and continue to face formal and informal barriers in access to education. In the 1960s, for example, a professor at Harvard in the 1960s turned down the future “Queen of RNA” Joan Steitz when she asked him to be her advisor: “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).[26]

Yet, women who were active scientists in 1956 were *more likely* than men to have PhDs. 84% of female academic scientists in 1956 had a PhD compared with just 78% of men (Table 4). This is consistent with a labor market that discriminates against women, requiring them to get better credentials than men to do the same job. Women also faced many formal and informal barriers that discouraged them to pursue PhDs. Parents of both genders were less likely to have a PhD: 83% of mothers had a PhD, compared with 84% of other women; 77% of fathers had a PhD, compared with 80% of other men.

5.2. Mothers Are Less Likely to Get Tenure Track Jobs

Mothers in academia were much less likely to get jobs as assistant professors, both compared with other women and fathers. Even among the scientists who were successful enough to survive in science and be recorded in the MoS (1956) just 35.9% became assistant professors (Table 4), and most of them remained instructors for their entire careers. By comparison, 44.6% of other women without children, and 45.4% of fathers found assistant professor jobs.

[25] These decisions create discriminatory equilibria under which gender stereotypes are self-confirming. Affirmative action, which is the focus of their paper, can ameliorate or intensify discrimination.

[26] 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).

Differences in tenure rack employment cannot be explained by mothers sorting into academia at a higher rate. While women are more likely work in academia overall, parents of both genders are less likely to take academic jobs (Appendix Figure A6). 84.5% of mothers enter academia compared with 73.9% of fathers and 88.6% of other women (Table 4).

Mothers also took much longer to become assistant professors, with an average of 4.4 years from PhD to assistant professor (and a median of 3), compared with just 1.3 years for fathers (median of 1) and 2.8 years for other women (median of 2). In contrast, fathers were slightly more likely to become assistant professors compared with other men and they advanced more quickly. Contemporary evidence indicates that these trends continue. Nelson and Rogers (2005) show that a smaller percentage of women doctorates continued to be hired into faculty positions as recently as the 2000s.

5.3. Female Scientists are Less Likely to Marry, and they Marry Late

Patent data indicate that mothers who survived in science were positively selected. Patent data show that female scientists who chose to marry were slightly *more* productive by 27 (the median age of marriage) than other women. 0.64% of married women had at least one patent by age 27 compared with just 0.57% of other women.[27]

Female scientists, however, were less than half as likely to marry compared with men. Just 38.8% of female scientists married, compared with 84.2% of men. The share of married women among female scientists increased over time, but it always stayed below the share of married men. Among the oldest cohort of scientists (above the age of 40 in 1945), only 29.7% of female scientists were married, compared with 79.1% of male scientists. Among the cohort of baby boom parents (scientists who were in their 20s in 1945), 51.0% of female scientists married, compared with 87.7% of men (Appendix Figure A9, Panel A).

Modern data indicate that delaying motherhood can improve a woman's career. Miller (2011), for example, shows that each year of delay increases work hours by 6%, earnings by 9%, and wages by 3%, with larger increases for college-educated women and those in professional and managerial occupations.

[27] There is also no evidence for pre-marriage productivity differences between married and unmarried men: 9.1% of married men and 9.3% of unmarried men had applied for at least 1 patent by age 27.

Anticipating findings for modern data, women who survived in science married much later than other women in the population. The US Census (1960) estimated that the median US woman married at age 20.9 years, while the median men married at age 22.8 years. 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 later than male scientists (Appendix Figure A8). Women in the oldest cohort (40 and above in 1945) married at a median age of 30 (and an average of 31.2), 2 years after 28, the median age of marriage for men (an average of 30.0). Among the baby boom parents, women married at a median age of 26 (and an average of 26.3), 1 year after the median age at marriage for men (25 years and an average of 25.6).

5.4. Selection into Parenting

We uncover no systematic evidence to suggest that mothers were less productive than other female scientists. In fact, mothers were more likely to have patented than single women without kids (with shares of 9.5 and 8.1%, Table 1), but slightly less likely than married women without kids (9.7%). Mothers also had more patents on average than other women without children (with 65 and 47 patents per 100 scientists, respectively). However, mothers less likely to have patented by age 27, the median age of marriage (0.40% for mothers compared with 0.65% of other women).

Yet, across all years, female scientists were less than one third as likely to have children compared with men. 22.1% of women who were scientists in 1956 had children, compared with 74.0% of men. While it became more common for female scientists to have children over time, female scientists were always less likely to have children compared with men (Appendix Figure A9, Panel B). For women, the share of parents among all scientists increased from 17.0% of women aged 40+ years in 1945 to 29.0% for women in their 20s. For men, the share of parents increased only slightly, from 71.5% to 74.8%.[28]

Female scientists also had many fewer children, with 0.41 children per female scientist, compared with 1.69 per male scientist (Appendix Figure A9, Panel C). Conditional on having any children, men had 2.3 compared with 1.9 for women (Appendix Figure A9, Panel D), again indicating that the most salient decision about parenting is at the extensive margin, between having any children or none.

The mothers of the baby boomers had more children than earlier cohorts, but still many fewer than male scientists. Women who were in their 20s at the beginning of the baby boom had 0.55 children per scientist, compared with just 0.31 for women in their 40s (Appendix Figure A9, Panel C). Male scientists had 1.6-1.7 children with minimal changes over time.

5.5. Selection into Research Fields

A potential explanation for the low patenting rates of women is that, anticipating their future fertility, women may select into fields that are less productive in terms of patents or publications. Examining the career costs of children at the opposite end of the skill spectrum, for women who pursue the non-college vocational track, Adda Dustmann and Stevens (2017), for example, find that both skill atrophy and selection into child-friendly occupations contribute to the career costs of children.[29] Importantly, selection cannot explain the time pattern of productivity for mothers, which is at the core of our empirical strategy. (It would require mothers anticipating the output of fields more 15 years ahead of time and choose fields that will be more productive then).

Nevertheless, we examine the influence of selection on differences in *levels* of output (for which we control in the main analysis. Methodologically, we apply *k*-means clustering to assign each scientist to a unique field based on the words that describe their discipline and research topics, and then compare output in terms of both patents and publications for fields with low and high shares of women.

[28] Some of these low rates of parenting may be due to the lack of role models with children. La Ferrara, Chong, and Duryea (2012) show that in Brazil, exposure to soap operas where the majority of the main female characters had either no children or only one child significantly decreased women's fertility.
[29] Adda et al (2017) examine German women who choose to attend lower-track (non-college preparatory) schools at age 10 (about two thirds of each cohort). After their high school graduation (around the age of 15-16) these women enroll to a 2-3 vocational training program that sets the path for their future career (before having children).

This analysis indicates that women were just slightly less likely to work in patent-intensive fields (Appendix Figure A14), which suggests that selection into fields cannot explain low patenting rates for female scientists. The correlation between the share of scientists in a field and the number of patents per scientists in that field is negative for women (at -0.1713), and very close to zero.

It is also notable that parenting had no noticeable influence on scientists' selection into fields. X-ray crystallography had a larger share of mothers (2.4% compared with 0.8 for other women, Appendix Figure A11), while mathematical analysis, which had a smaller share of mothers (2.4% compared with 5.8% for other women), but these differences may be random. For fathers and other men, the largest differences occur in distillation, which had a larger share of fathers (3.2% compared with 2.7 for other men, Appendix Figure A12) and mathematical analysis, which had a smaller share of fathers (1.8% compared with 2.5% for other men).
More generally women may select into fields that are less competitive (Niederle and Vesterlund 2007)[30] or more "family friendly" (Goldin 2014, Goldin and Katz 2016, Adda, Dustmann, and Stevens 2017). Historians of American science have used selection and preferences to rationalize the underrepresentation of women in American physics. Kevles (1971, p. 371) explains

> …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.

In contrast with this traditional view of American science, we find that women who survived in science were over-represented in physics: 3.7% of female scientists worked in physics, more than six times compared with a 0.6% share of men (Appendix Figure A11). Other fields with high shares of women were chemistry (16.2% of female scientists, 11.5% of men), protein (6.9% female, 2.0 male), mathematical analysis (5.0% female scientists, 2.0% male), and radiation (3.7% of female scientists and 4.5% male).[31] The disproportionate representation of women in physics, mathematical analysis, and other technical fields may reflect the costs of discrimination

[30] Niederle and Vesterlund (2007) conduct a laboratory experiment in which men and women solve a real task, first under a non-competitive piece rate and then a competitive tournament incentive scheme. Although they show no gender differences in performance, men select into the competitive scheme twice as much compared with women.
[31] The prominence of women in mathematical analysis and physics is striking, particularly considering the considerable barriers to entry faced by women.

in fields that depend on rare talents. In those fields the "price of prejudice" (Hedegaard and Tyran 2018; Becker 1957) may have been too high to prevent the entry of women scientists.[32]

5.6. Selection into "Surviving" as a Scientist

Patent data indicate that mothers become *more* productive after age 35 and after the first 15 years of marriage, while other scientists became less productive during those periods. A possible explanation for this finding is that mothers had to be truly exceptional to survive in STEM. To investigate selection into survival, we match scientists in the MoS (1956) with faculty records of major universities. As a first step, we have digitized the faculty rosters of Columbia University and combined these data with existing records from the UC Cliometric History Project for Stanford University, UCLA, and UC Berkeley from 1943 to 1945 to capture pre-baby boom stock of scientists across these major universities.[33] We then use a combination of algorithmic and manual matching to identify scientists who were recorded in the MoS (1956).[34]

Linking the MoS with faculty records confirms that women were much less likely to survive in science compared with men. Among 808 women who were faculty members between 1943 and 45, only 79 (9.8%) survived to enter the MoS in 1956 (Table 5). In contrast, 793 (19.8%) of 4,003 male professors at the same universities survived to enter the MoS (1956). Just 20 (25.3%) of the 79 surviving scientists were mothers, compared with 584 (73.6%) of 793 surviving male scientists (Table 5).

VI. A MISSING COHORT OF BABY BOOM MOTHERS

In this final section we investigate the aggregate effects of high fertility rates and "family values" during the baby boom on participation and gender inequality in science. Historically, children have discouraged female labor force participation (e.g., Aaronson et al forthcoming).[35] Did the effects of children during the baby boom help create the dearth of female scientists? To

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[32] Becker (1957) describes the costs of prejudice in a chapter on "price and prejudice." Hedegaard and Tyran (2018) present experimental evidence, which shows that discriminators respond to the cost of prejudice in terms of lost wages when they choose a less productive co-worker on ethnic grounds.
[33] Faculty records for the California universities were obtained from the UC ClioMetric History Project (http://uccliometric.org/faculty/, accessed August 1, 2020.
[34] 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%).
[35] Examining data from 441 censuses and surveys across 103 countries between 1787 and 2015 Aaronson et al (forthcoming) show that fertility has large and robust negative effects on female labor supply for wealthier countries (but no effects for poorer countries) both historically and today.

help answer this question, we examine gender differences in participation (and entry into science) across birth cohorts.[36] These data reveal a large decline in participation and entry by women at the beginning of the baby boom in 1946. Notably, this decline was driven by women who were of prime child-bearing age – between 20 and 29 – at the beginning of the baby boom.

Figure 7 presents the birth cohorts and gender of American scientists in 1956. These data indicate that women born before 1915 made significant progress towards closing the gender gap in STEM (Figure 7). Starting from 1865, participation by female scientists increased 113-fold from just one female scientist born in 1865 to 113 born in 1898, while participation by male scientists increased 67.4-fold from 16 male scientists born in 1865 to 1,062 in 1898. After 1898, female participation remained stable around 110 female scientists per birth year, while the number of male scientists more than doubled to 2,432 male scientists born in 1915.

For women born after 1915, participation declines both in absolute and relative terms (Figure 7). American scientists in the MoS (1956) include 118 female scientists born in 1915, but 93 women born in 1921. Notably, the decline in participation affects women who were 24 years old in 1945, close to the median age of childbearing during the baby boom. A comparison with rates of entry for male scientists shows that the decline in entry was limited to women. While fewer women entered US science, the number of male scientists increased steadily to 2,528 scientists born in 1921.

An estimated 177 women in the generation of baby boom mothers were missing from American Science by 1956. For birth cohorts 1900-15, 110 women were active in American science in 1956. For birth cohorts 1916-25, who would have been in their 20s at the beginning of the baby boom, just 92.3 women were active in American science by 1956. Had women in the generation of baby boom mothers participated in US science at the same rate, a counterfactual total of 1100 women scientists born from 1916-1925 would have been active in US science, 177 more compared with the 923 women observed in the data.

Changes in the share of women among new scientists per year indicate that women's participation increased between 1930 and 1945 but declined afterwards (Appendix Figure A18,

[36] We use the year of the scientist's first university enrollment or first job to determine when they entered US science. These data are available for 80,965 of 82,094 American scientists (98.6%, Moser and San 2020).

Panel A).[37] Between 1930 and 1945, the share of women scientists grew from 6.9% to 9.3%. After 1945, however, it declined dramatically to 4.4 in 1947 and 3.2 in 1949.

This decline was driven by women in the cohort of baby boom mothers, who were in their 20s in 1945. The share of women in this cohort among all new American scientists declines from a peak of 7.0% in 1945 to just 2.1% in 1950 and 1.6% in 1953. The next most affected cohort were women who were in their 30s in 1945, whose share declines from 1.7% in 1945 to 1.0% in 1950 and 0.3% in 1952.

VII. Conclusions

Our analysis of biographical data and output measures for more than 82,000 American indicates that the disproportionate burden of parenting may be an important driver of underrepresentation and gender inequality in science. Using patents and publications to examine variation in scientists' productivity across the life cycle, we show that mothers are less productive in their 20s and early 30s but experience a large boost in productivity in their late 30s and early 40s, long after the productivity of other scientists has started to decline. Event studies of marriage show that mothers experience a large increase in output 15 years after marriage, at a time when the time requirements of raising children become less intense. Importantly, this late-in-marriage increase in productivity is unique to mothers and not shared by fathers or other scientists.

Differences in the timing of productivity have important implications for tenure rates and participation in science. We find that just 27% of mothers who are academic scientists get a tenured job compared with 48% of fathers and 46% of women without children. Analyzing the speed of promotion we show that mothers fall behind other scientists starting in the fifth year after starting an assistant professor position. Event studies of marriage indicate that a mother's probability of holding a tenured job declines with each additional year of marriage. At the same time, tenure rates for fathers and other married men increase with each additional year. These findings suggest that – when mothers carry a disproportionate share of childbearing and chil-rearing responsibilities – gender-neutral tenure policies for parents have held back female scientists. Some of these differences persist to this day. Examining data for the universe of assistant professor hires at top-50 economics departments between 1980 and 2005, Antecol,

[37] Active scientists are defined as scientists who were of working age (between 18 and 80) in in a given year *t*.

Bedard, and Sterns (2018), for example, find that gender-neutral tenure clock stopping policies have substantially reduced female tenure rates while increasing tenure rates for men.

If tenure decisions accurately reflect a scientist's predicted productivity, regardless of their economic status, changes in productivity after tenure should be comparable across demographic groups. Yet, our event studies of publications after tenure show that mothers publish more after tenure, while all other scientists publish less. Life cycle analyses of publications further show that mothers who achieve tenure experience a boost in productivity in their early 40s. Even mothers who do not get tenure sustain high levels of productivity into their mid 50s. These results suggest that current tenure processes may be biased against mothers, whose early output is a poor predictor of life-time productivity.

Historically, women have internalized the career costs of children by delaying marriage and foregoing children (e.g. Goldin 2014). Compared with male scientists, female scientists were half as likely to marry, with marriage rates of just 40% compared with 80% for men. Less than one in four female American scientists had children (22%) compared with three in four male scientists.

Since the 1950s, women have caught up in many dimensions of education and employment, but they continue to be underrepresented in science. Women who were born in the 195s and came of age in the 1970s narrowed the gender gap in college attendance and graduation, in the attainment of professional degrees, and in employment in nontraditionally female occupations (Goldin 2006). Since the late 1980s, national committees and professional organizations have initiated programs to increase female participation in science and engineering (American Council on Education 1988; National Research Council 1991), resting on the belief that increasing the talent pool will lead to more women choosing careers in STEM (Chesler and Chesler 2002). Yet, these programs have not led to a proportional increase in women faculty (Barber 1995; Frehill et al. 2006; Kulis et al. 2002; Nelson and Rogers 2005; NSF 2003; Pell 1996).

Our results suggest that differences in the timing of productivity as a result of children are an important source of persistent under-representation for women in science. Analyzing detailed employment data, we document that the mothers of the baby boom were lost to US science. Their absence as role models and mentors to future generations may affect science to this day.

References

U.S. Bureau of Labor Statistics. 2018 and 2019. *American Time Use Survey.* Last updated June 20, 2020.

Adda, Jerome, Christian Dustmann, and Katrien Stevens, "The Career Costs of Children," *Journal of Political Economy*, 125 (2017), 293–337.

Alon, Titan, Matthias Doepke, Jane Olmstead-Rumsey and Michèle Tertilt. 2020. "The Impact of Covid-19 on gender equality." *Covid Economics*, *CEPR*, Issue 4, April 14, 2020, pp. 62-85.

Antecol, Heather, Kelly Bedard and Jenna Stearns. "Equal but Inequitable: Who Benefits from Gender-Neutral Tenure Clock Stopping Policies?" *American Economic Review*, Volume 108, No. 9, September 2018, pp. 2420-41.

Aaronson, Daniel, Rajeev Dehejia, Andrew Jordan, Cristian Pop-Eleches, Cyrus Samii, and Karl Schulze. Forthcoming. "The Effect of Fertility on Mothers' Labour Supply over the Last Two Centuries." *Economic Journal.*

Altonji, Joseph G. and Rebcca Blank. "Race and Gender in the Labor Market" in Orley Ashenfelter and David Card, (eds), *Handbook of Labor Economics Volume* 3c Elsevier Science B.V. (1999): 3144-3259.

Bailey, Martha J. 2006. "More Power to the Pill: The Impact of Contraceptive Freedom on Women's Life Cycle Labor Supply" *The Quarterly Journal of Economics*, Vol. 121, Issue 1, February, pp. 289–320.

Barber, Leslie A. 1995. "U.S. women in science and engineering, 1960-1990: Progress toward equity?" *Journal of Higher Education*, 66(2), pp. 213-234.

Becker, Gary S. 1957. *The Economics of Discrimination*. Chicago: University of Chicago Press.

Becker, Gary S. 1991. *A Treatise on the Family, Enlarged Edition*. Cambridge: Harvard University Press.

Bertrand, Marianne, Claudia Goldin, and Lawrence F. Katz. 2010. "Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors." *American Economic Journal: Applied Economics.* Vol. 2, July, pp. 228-55.

Blau, Francine D. and Lawrence M. Khan, 1997. "Swimming Upstream: Trends in the Gender Wage Differential in the 1980s." *Journal of Labor Economics,* 15 (1, part 1): pp. 1-42.

Brown, Charles and Mary Corcoran, 1997. "Sex-Based Differences in Scholl Content and the Male-Female Wage Gap." *Journal of Labor Economics,* 15(3), pp. 431-465.

Cattell, Jacques, 1956. *American Men of Science: A Biographical Directory. Volumes I- III.* New York: R. R. Bowker Company.

Cattell, Jacques, 1957. *Directory of American Scholars: A Biographical Directory*. Garrison, NY: Science Press.

Centers for Disease Control and Prevention. *Vital Statistics of the United States, 2003, Volume I, Natality,* Table 1-1 "Live births, birth rates, and fertility rates, by race: United States, 1909-2003. https://www.cdc.gov/nchs/data/statab/natfinal2003.annvol1_01.pdf.

Coate, Stephen and Glenn Loury, 1993. "Will Affirmative Action Policies Eliminate Negative Stereotypes?" American Economic Review, 83(5), pp. 1120-1240.

Chesler, Naomi C., and Mark A. Chesler, 2002. "Gender-Informed Mentoring Strategies for Women Engineering Scholars: On Establishing a Caring Community." *Journal of Engineering Education*, 91, pp. 49-55.

Cohen, Wesley M., Richard R. Nelson and John P. Walsh, 2000. "Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not)" NBER Working Paper No. 7552, Issued in February 2000.

Davis, Steven J. and Till von Wachter. "Recessions and the Costs of Job Loss." Brookings Pap Econ Act. 2011 Fall; 2011(2): 1–72.

Doepke, Matthias, Moshe Hazan and Yishay D. Maoz.2015. "The Baby Boom and World War II: A Macroeconomic Analysis.' Review of Economic Studies, vol. 82, pp. 1031-73.

Frehill, Lisa, Abby Javurek-Humig and C. Jeser-Cannavale. 2006. "Women in Engineering: A review of the 2005 literature." *Magazine of the Society of Women Engineering,* 52(3), pp. 34-63.

Goldin, Claudia D. 1990. *Understanding the Gender Gap. An Economic History of American Women*. New York and Oxford: Oxford University Press.

Goldin, Claudia D. 1991. "The Role of World War II in the Rise of Women's Employment." *The American Economic Review*, Vol. 81, Issue 4, September, pp. 741-56.

Goldin, Claudia D. 2006. "The Quiet Revolution that Transformed Women's Employment, Education, and Family." *The American Economic Review* Vol. 96, No. 2, May, pp. 1-21

Goldin, Claudia D., 2014. "A Grand Gender Convergence: Its Last Chapter." *The American Economic Review*, 104(4), pp. 1091-1119.

Goldin, Claudia D., and Lawrence F. Katz. 2002. "The Power of the Pill: Oral Contraceptives and Women's Career and Marriage Decisions." *Journal of Political Economy* 110 (4), pp. 730–70.

Goldin, Claudia D., and Lawrence F. Katz, 2016. "A Most Egalitarian Profession: Pharmacy and the Evolution of a Family-Friendly Occupation." *Journal of Labor Economics*, 34 (3), pp. 705-745.

Guvenen, Fatih, Fatih Karahan, Serdar Ozkan and Jae Song. 2017. "Heterogeneous Scarring Effects of Full-Year Nonemployment." *American Economic Review Papers and Proceedings.* 107(5):369-73.

Hedegaard, Morten Størling and Jean-Robert Tyran. 2018 "The Price of Prejudice" *American Economic Journal: Applied Economics*, 10(1), pp. 40-63.

Jacobson, Louis, Robert LaLonde and Daniel Sullivan. (1993). Earnings losses of displaced workers. *American Economic Review*, pp. 685-709.

Jarosch, Gregor. 2015. "Searching for Job Security and the Consequences of Job Loss." Working paper. Princeton University.

Jensen, Kyle, Balázs Kovács and Olav Sorenson. 2018. "Gender differences in obtaining and maintaining patent rights" *Nature Biotechnology.* Vol 36, pp. 307–309.

Kevles, Daniel J. 1995. *The Physicists. The History of a Scientific Community in Modern America. With a Preface by the Author*, 2nd edition.

Kleven, Henrik, Camille Landais, and Jakob Egholt Søgaard. 2019. "Children and Gender Inequality: Evidence from Denmark." *American Economic Journal. Applied Economics*, Vol. 11, No. 4, October, pp. 191-209.

Kleven, Henrick, Camille Landais, Johanna Posch, Andreas Steinhauer, and Josef Zweimüller. 2019. "Child Penalties across Countries: Evidence and Explanations." *AEA Papers and Proceedings*, Vol. 109, May, pp. 122-26.

Kuka, Elira and Na'ama Shenav, 2020. "Long-Run Effects of Incentivizing Work After Childbirth", Working Paper.

Kulis, Stephen, Diane Sicotte and Shawn Collins. 2002. "More than a pipeline problem: Labor supply constraints and gender stratification across academic science disciplines." *Research in Higher Education*, 43(6), pp. 657-690.
Levenshtein, Vladimir, 1966. "Binary codes capable of correcting deletions, insertions, and reversals." *Soviet Physics Doklady*. 10 (8), February, pp. 707-10.
Lundberg, Shelly, and Elaina Rose. 2000. "Parenthood and the Earnings of Married Men and Women." *Labour Economics* 7 (6): 689–710.
Lucci-Canapari, Jeanna. 2019. "Special Symposium Honors Steitz, Illuminates Challenges that Women Scientists Face" Yale School of Medicine, Press Release, March 18.
MacDonald, G. and Weisbach M.S. 2004. "The Economics of Has-Beens." *Journal of Political Economy*, 112 (S1), pp. 289-310.
Martell, Michael and Peyton Nash. 2020. "For Love and Money? Earnings and Marriage Among Same-Sex Couples" *Journal of Labor Research* 41(2).
McDowell, John M. "Obsolescence of Knowledge and Career Publication Profiles: Some Evidence of Differences Among Fields in the Cost of Interrupted Careers." *The American Economic Review* 72(4) pp. 752-68.
McDowell, John M., Larry D. Singell, and James P. Ziliak, 1999. "Cracks in the Glass Ceiling: Gender and Promotion in the Economics Profession." *The American Economic Review*, 89(2), pp. 392-396.
Miller, Amalia R. 2011. "The Effects of Motherhood Timing on Career Path." *Journal of Population Economics* 24 (3): 1071–1100.
Moser, Petra, 2012. "Innovation without Patents – Evidence from World's Fairs." *The Journal of Law and Economics*, Volume 55, No. 1, February 2012, pp. 43-74.
Moser, Petra and Shmuel San, 2020. "Immigration, Science, and Invention. Lessons from the Quota Acts." Working paper, New York University.
Moser, Petra and Sahar Parsa. "Reducators. How Joseph McCarthy Changed American Science." Working paper, New York University.
Mundy, Liza. 2018. *Code Girls. The Untold Story of the American Women Code Breakers of World War II.* New York: Hachette Books.
Myers, Kyle R.,Wei Yang Tham, Yian Yin, Nina Cohodes, Jerry G. Thursby, Marie C. Thursby, Peter Schiffer, Joseph T. Walsh, Karim R. Lakhani and Dashun Wang. "Unequal effects of the COVID-19 pandemic on scientists." *Nature Human Behavior*, Vol. 4, September, pp. 880-8.
National Academy of Science. 2006. *Beyond Bias and Barriers: Fulfilling and Potential of Women in Academic Science and Engineering.* Washington DC: National Academies Press.
National Science Foundation, Arlington, Va. Div. of Science Resources Statistics. 2002. *Women, minorities, and persons with disabilities in science and engineering.* Available at https://www.nsf.gov/statistics/women/.
Nelson, Donna and Diana Rogers. 2004. *A national analysis of diversity in science and engineering faculties at research universities.* University of Oklahoma, Department of Chemistry.
Neal, Derek. 1995. Industry-specific Human Capital: Evidence from Displaced Workers. *Journal of Labor Economics,* 13 (4), pp. 653-677.

Niederle, Muriel and Lise Vesterlund. “Do Women Shy Away from Competition? Do Men Compete Too Much? *The Quarterly Journal of Economics.* Volume 122, Issue 3, August, pp. 1067-1101.

Paglin, Morton and Anthony Rufolo. “Heterogeneous Human Capital, Occupational Choice, and Male-Female Earnings Differences.” *Journal of Labor Economics*. 8(1), pp. 123-144.

Pell, Alice N. 1996. “Fixing the leaky pipeline: women scientists in academia.” *Journal of Animal Science*, 74, pp. 2843-2848.

Settles, Isis H., Lilia M. Cortina, and Janet Malley. 2006. “The climate for women in academic science: The good, the bad, and the changeable*.” Psychology of Women Quarterly*, 30 pp. 47-58.

Shaw, Alison K., and Daniel E. Stanton. Leaks in the pipeline: separating demographic inertia from ongoing gender differences in academia. Proc Roy Soc B. 2012; 279: 3736–3741.

Sheltzer, Jason M., and Joan C. Smith. Elite male faculty in the life sciences employ fewer women. PNAS. 2014; 111: 10107–10112. https://doi.org/10.1073/pnas.1403334111 PMID: 24982167

Shetterly, Margot Lee. 2016. *Hidden Figures: The American Dream and the Untold Story of the Black Women Mathematicians Who Helped Win the Space Race.* New York, NY: William Morrow and Co.

Sonnert, Gerhard and Gerald Holton. 1996. “Career patterns of women and men in the sciences.” *American Scientist*, 84(1), pp. 63-71.

Topel, Robert H. and Michael P. Ward. 1992. “Job Mobility and the Careers of Young Men.” *The Quarterly Journal of Economics.* Vol. 107, No. 2, May, pp. 439-479.

U.S. Census Bureau. *2020 Census Will Help Policymakers Prepare for the Incoming Wave of Aging Boomers.* https://www.census.gov/library/stories/2019/12/by-2030-all-baby-boomers-will-be-age-65-or-older.html.

U.S. Census Bureau. *Estimated Median Age at First Marriage, by Sex: 1890 to Present.* https://www.census.gov/population/socdemo/hh-fam/tabMS-2.pdf

van Noorden, Richard, Brendan Maher, Brendan and Regina Nuzzo. 2014. “The Top 100 Papers” *Nature*, Volume 514, Issue 7524, October, pp. 550-553 (2014).

Waldrop, M. Mitchell. "Why we are teaching science wrong, and how to make it right." *Nature*. 523 (7560), pp. 272–274.

Weiss, Jessica. 2000. *To Have and to Hold. Marriage, the Baby Boom & Social Change.* Chicago and London: The University of Chicago Press.

Winkler, William E. 2006. "Overview of Record Linkage and Current Research Directions." US Census, Research Report Series, RRS.

TABLE 1 – SUMMARY STATISTICS ON MARRIAGE, PARENTING, AND INVENTION

	All women	All men	Women		Men	
			with children	w/o children	with children	w/o children
Demographics:						
N	4,032	66,198	892	3,140	48,987	17,211
Share married (in %)	38.8	84.2	93.3	23.4	95.6	51.9
Age at marriage	28.8	27.6	27.1	30.8	27.2	29.8
	(6.55)	(5.21)	(5.01)	(7.48)	(4.78)	(6.60)
Share parents (in %)	22.1	74.0	100	0	100	0
Children per scientist	0.41	1.69	1.88	0	2.28	0
	(0.88)	(1.35)	(0.89)		(1.05)	
Scientific Productivity:						
Patents per scientist	0.51	3.58	0.65	0.47	3.82	2.83
	(3.58)	(11.74)	(5.80)	(2.67)	(12.43)	(9.30)
Publications per scientist	5.14	7.14	5.39	5.06	7.23	6.89
	(10.38)	(15.96)	(11.67)	(9.98)	(16.36)	(14.75)
Citations per publication	27.21	103.50	41.99	23.10	123.99	36.03
	(124.84)	(1,596.14)	(200.37)	(91.79)	(1,812.36)	(343.27)

Notes: Summary statistics on marriage, parenting, and patenting for 70,230 American scientists in the MoS (1956). *Share married* divides the number of married scientists by the total number of scientists. *Age at marriage* is calculated by subtracting the scientist's birth year from their year of marriage, which is reported in the MoS (1956). *Share parents* divides the number of scientists who have at least one child in 1956 by the total number of scientists; *children per scientist* reports the number of children per scientist. *Patents per scientist* divides the total number of patents issued to scientists in STEM (chemistry, mathematics, and other STEM fields) by the total number of scientists in STEM. *Publications per scientist* divides the total number of publications in Microsoft Academic Graph (MAG) matched with scientists in the MoS (1956) by the total number of scientists in the MoS (1956). *Citations per publication* divides the total number of citations in MAG matched with scientists in STEM in the MoS (1956) by the total number of publications.

TABLE 2 – PRODUCTIVITY MEASURED BY PATENTS

	Patents					
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-5.870***	-5.627***	-5.245***	-2.432***	-2.503***	-2.189***
	(0.173)	(0.174)	(0.156)	(0.067)	(0.067)	(0.061)
Parent	1.772***	1.898***	1.675***	1.186***	1.098***	1.089***
	(0.135)	(0.138)	(0.125)	(0.068)	(0.068)	(0.063)
Female*Parent	-0.912**	-1.090***	-1.293***	-0.847***	-0.795**	-0.924***
	(0.389)	(0.391)	(0.366)	(0.125)	(0.125)	(0.116)
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	8.811	8.811	8.752	4.606	4.606	4.579

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

Notes: OLS estimates compare changes in the number of US patents by US scientists per year between 1930 and 1970. Column (1) estimates $y_{it} = \beta_1 Parent_i + \beta_2 Female_i + \beta_3 Female * Parent_i + \delta_t + \pi_b + \mu_f + \epsilon_{it}$, where the dependent variable y_{it} counts US patents per scientist i (multiplied by 100) in year *t*. The variable $Parent_i$ indicates scientists who were parents in 1956, $Female_i$ is an indicator for women, and $Female * Parent_i$ identifies mothers; δ_t are year fixed effects for years *t*, π_b are birth cohort fixed effects for birth years b, and μ_f are field fixed effects for fields *f*. Robust standard errors in parenthesis. Columns (1-3) estimate regressions for the physical sciences (STEM, including physics, mathematics, and engineering), Column (2) includes age fixed effects (and excludes cohort fixed effects). Column (3) extends the data to include older scientists up to age 80. Columns (4)-(6) include scientists in the biological sciences (biology and medicine), scientists in the social sciences (economics, psychology, and sociology), and scientists across all disciplines respectively.

TABLE 3 – PRODUCTIVITY MEASURED BY PUBLICATIONS AND CITATIONS

	Publications (1-6)						Citations (7-8)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-8.355***	-8.646***	-8.176***	-9.959***	-9.945***	-9.613***	-9.077***	-9.072***
	(0.258)	(0.256)	(0.235)	(0.197)	(0.196)	(0.181)	(2.215)	(2.318)
Parent	1.028***	0.491***	1.160***	0.829***	-0.609***	0.977***	14.091***	14.411***
	(0.138)	(0.133)	(0.131)	(0.114)	(0.111)	(0.107)	(4.234)	(4.196)
Female*Parent	-1.108**	-0.811*	-0.982**	-0.353	-0.321	-0.442	-9.248***	-10.742***
	(0.474)	(0.470)	(0.454)	(0.411)	(0.410)	(0.387)	(3.354)	(3.879)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth year FE	Yes	No	Yes	Yes	No	Yes	Yes	No
Age FE	No	Yes	No	No	Yes	No	No	Yes
Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Disciplines	STEM	STEM	STEM	All	All	All	STEM	STEM
Scientists' age	18-65	18-65	18-80	18-65	18-65	18-80	18-65	18-65
N (scientists x years)	1,204,592	1,204,592	1,298,053	2,391,179	2,391,179	2,591,524	1,204,592	1,204,592
Pre-baby boom mean	11.189	11.189	11.208	15.832	15.832	15.862	21.275	21.275

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

Notes: OLS estimates of changes in productivity, measured by author-weighted publications per 100 scientists (columns 1-6) and citations per scientist (columns 7-8) per year between 1930 and 1970. Column (1) estimates $y_{it} = \beta_1 Parent_i + \beta_2 Female_i + \beta_3 Female * Parent_i + \delta_t + \pi_b + \mu_f + \epsilon_{it}$, where the dependent variable y_{it} counts publications per scientist i (divided by the number of authors per publication, multiplied by 100) in year *t*. The variable $Parent_i$ indicates scientists who were parents in 1956, $Female_i$ is an indicator for women, and $Female * Parent_i$ identifies mothers; δ_t are year fixed effects for years *t*, π_b are birth cohort fixed effects for birth years *b*, and μ_f are field fixed effects for fields *f*. Columns (1-3) estimate regressions for the physical sciences (STEM (including physics, mathematics, and engineering), Column (2) includes age fixed effects (and excludes cohort fixed effects). Column (3) extends the data to include older scientists up to age 80. Columns (4)-(6) include scientists in the biological sciences (biology and medicine), scientists in the social sciences (economics, psychology, and sociology), and scientists across all disciplines respectively. Columns (7)-(8) estimate the same regressions as columns (1)-(2), but instead use citations per scientist *i* (divided by the number of authors per publication) in year *t* as the independent variable.

TABLE 4 – SUMMARY STATISTICS ON PARTICIPATION AND CAREER PROGRESSIONS FOR ACADEMIC SCIENTISTS

	All women	All men	Women		Men	
			with children	w/o children	with children	w/o children
N	4,032	66,198	892	3,140	48,987	17,211
Academic / all scientists	87.7%	74.6%	84.5%	88.6%	73.8%	77.1%
PhD / academic scientists	84.1%	77.5%	83.2%	84.4%	76.6%	79.8%
Tenure track / academic scientists	42.7%	45.5%	35.9%	44.6%	45.4%	45.9%
Tenured / academic scientists	41.7%	47.7%	26.8%	45.7%	47.8%	47.2%

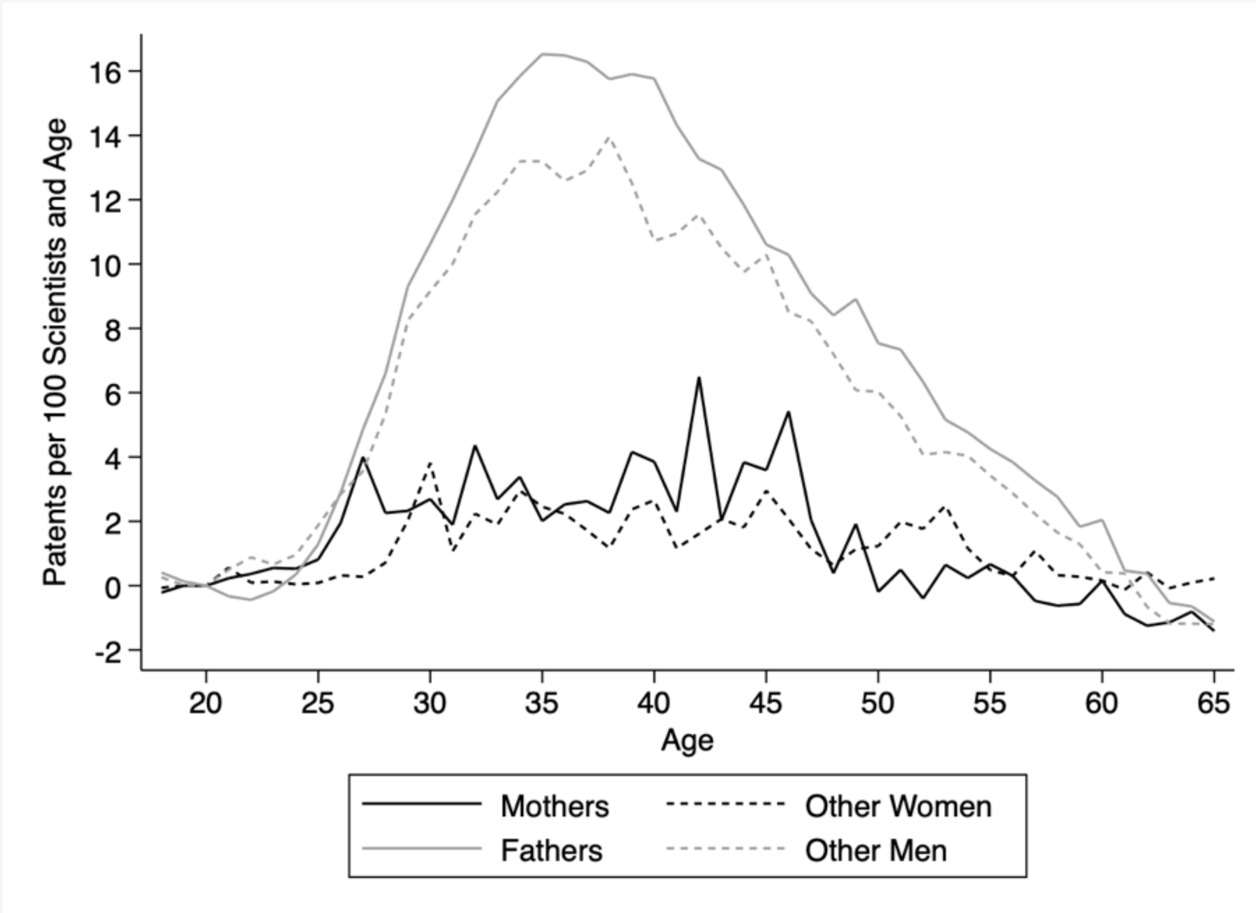
Notes: Summary statistics on participation in academia for 70,230 American scientists in the MoS (1956). *Academic / All Scientists* divides the number of academic scientists (identified by their employment records) by the total number of scientists. *PhD / Academic Scientists* divides scientists with PhDs by the total number of academic scientists. *Tenure track / Academic Scientists* divides the number of assistant professors by the total number of academic scientists. *Tenured / Academic Scientists* divides the number of associate and full professors (excluding visiting associate and full professors) by the total number of academic scientists.

TABLE 5 – SURVIVAL IN ACADEMIC SCIENCE

	All	All women	All men	Women with children	Women w/o children	Men with children	Men w/o children
Surviving faculty:							
N	872	79	793	20	59	584	209
Columbia	385	46	339	11	35	255	84
Stanford	166	7	159	3	4	123	36
UC Berkeley	240	16	224	5	11	158	66
UCLA	95	12	83	1	11	57	26
Demographics:							
Age in 1956	56.1	56.7	56.0	53.7	57.7	55.4	58.0
	(11.79)	(9.96)	(11.95)	(11.45)	(9.23)	(11.69)	(12.46)
Share married (in %)	77.9	43.0	81.3	90.0	27.1	91.6	52.6
Age at marriage	29.4	29.2	29.5	26.0	32.8	28.8	32.8
	(6.61)	(8.60)	(6.50)	(4.51)	(10.67)	(5.80)	(8.42)
Share parents (in %)	69.3	25.3	73.6	100	0	100	0
N children	1.63	0.49	1.74	1.95	0	2.36	0
	(1.38)	(0.95)	(1.37)	(0.83)		(1.03)	

Notes: To examine differences in the rate of survival among academic scientists we match faculty in directories before the baby boom, in 1943-45 with the MoS (1956). Faculty directories include 2,446 faculty at Columbia (including 387 women), 1,063 at Stanford (197 women), 897 at UC Berkeley (137 women), and 405 at UCLA (87 women). To construct these data, we digitized faculty directories for Columbia and accessed California universities from the UC ClioMetric History Project (http://uccliometric.org/faculty/ August 1 2020). 2 of 79 women and 12 of 793 men in the MoS (1956) switched jobs and were faculty at more than one university between 1943 and 1945. *Share married* divides the number of married scientists by the total number of scientists. *Age at marriage* is calculated by subtracting the scientist's birth year from their year of marriage. *Share parents* divides the share of scientists who had one or more children in 1956 by the total number of scientists. *N children* reports the number of children.

FIGURE 1 – AGE-VARYING ESTIMATES OF PRODUCTIVITY IN STEM, MEASURED BY PATENTS

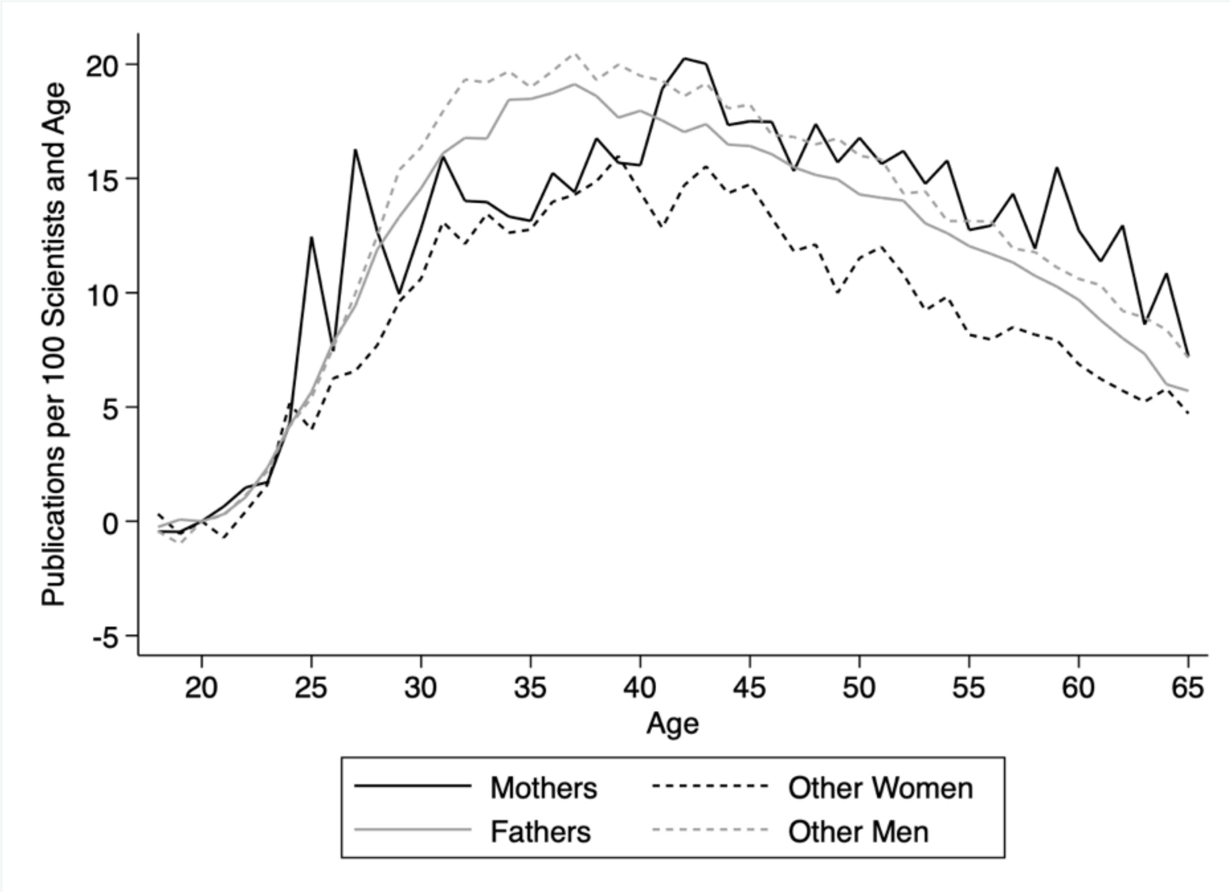


Notes: OLS estimates of β_a^d for demographic d (mothers, fathers, other women, and other men) in the equation $y_{ia}^d = \beta_a^d Age_i + \delta_t + \pi_y + \mu_f + \epsilon_{it}$ where y_{ia}^d are US patents per 100 scientists of demographic d in age a. The coefficient β_a^d is a vector of age-varying estimates of inventions created by 100 scientists of age a and demographic d compared with scientists in the same demographic at age 20. δ_t are patent application year fixed effects to capture variation in patenting over time; π_y are fixed effects for birth years y to control for variation in productivity across cohorts. Field fixed effects μ_f control for variation in patenting across fields. Data include 35,368 STEM scientists who were active in American science in 1956; 25,829 are fathers, 8,367 other men, 252 mothers, and 920 other women (without children).

FIGURE 2 – EVENT STUDIES OF CHANGES IN PATENTING IN STEM AFTER MARRIAGE

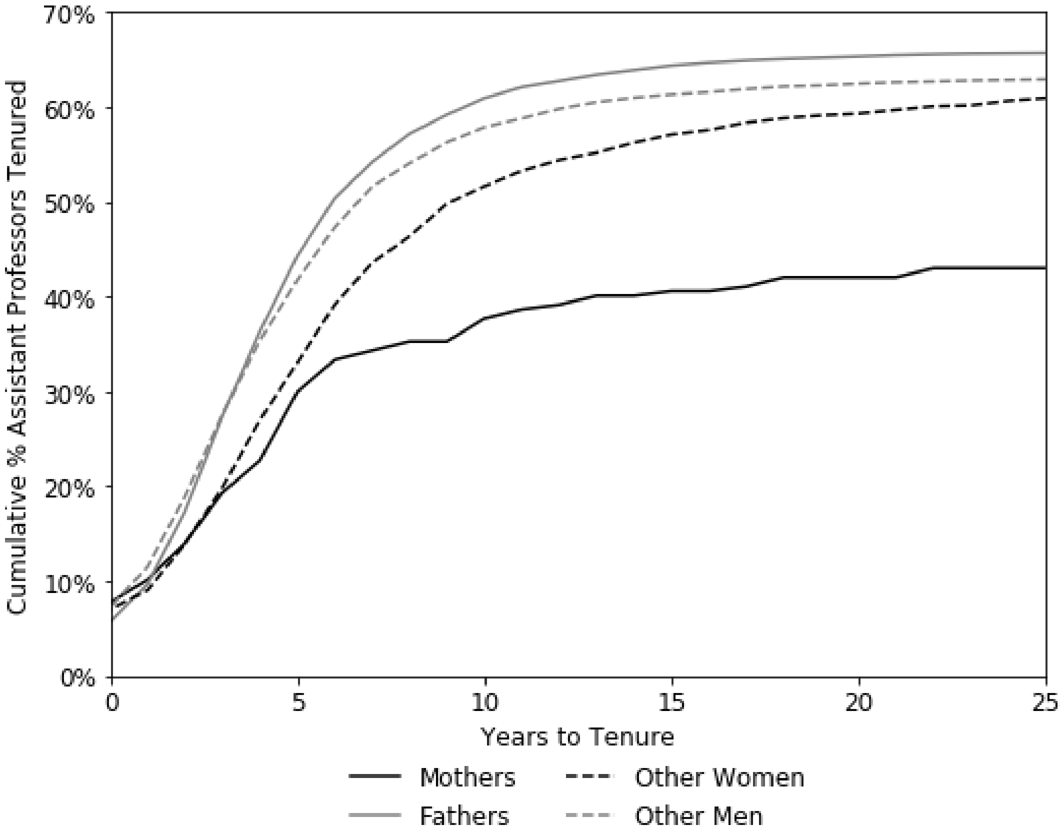
Notes: OLS estimates of β_s^d for demographic d (mothers, fathers, other married women, and other married men) in the equation $y_{is}^d = \beta_s^d EventTime_i + \delta_t + \alpha_a + \mu_f + \epsilon_{it}$ where y_{is}^d are patents per 100 scientist of demographic d and year s relative to the year of marriage. The coefficient β_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 they married. δ_t are patent application year fixed effects; α_a are scientist age fixed effects. Field fixed effects μ_f control for variation in patenting across fields *f*. Data include 29,954 married scientists working in STEM; 24,777 of them are fathers, 4,711 other married men, 239 mothers, and 227 other married women without children.

FIGURE 3 – AGE-VARYING ESTIMATES OF PRODUCTIVITY, MEASURED BY PUBLICATIONS



Notes: OLS estimates of β_a^d for demographic d (mothers, fathers, other women, and other men) in the equation $y_{ia}^d = \beta_a^d Age_i + \delta_t + \pi_y + \mu_f + \epsilon_{it}$ where y_{ia}^d are publications per 100 scientists of demographic d and age a. To account for co-authorships, we divide co-authored papers by the number of authors. The coefficient β_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. δ_t are publication year fixed effects; π_y are fixed effects for birth years y to control for variation in productivity across cohorts. Field year fixed effects μ_f control for variation in the number of publications across fields *f*. Data include 70,230 scientists across all fields (including STEM, the biological sciences, and the social sciences); 48,987 of them are fathers, 17,211 other men, 892 mothers and 3,140 other women without children.

FIGURE 4 – SPEED OF PROMOTION TO TENURE

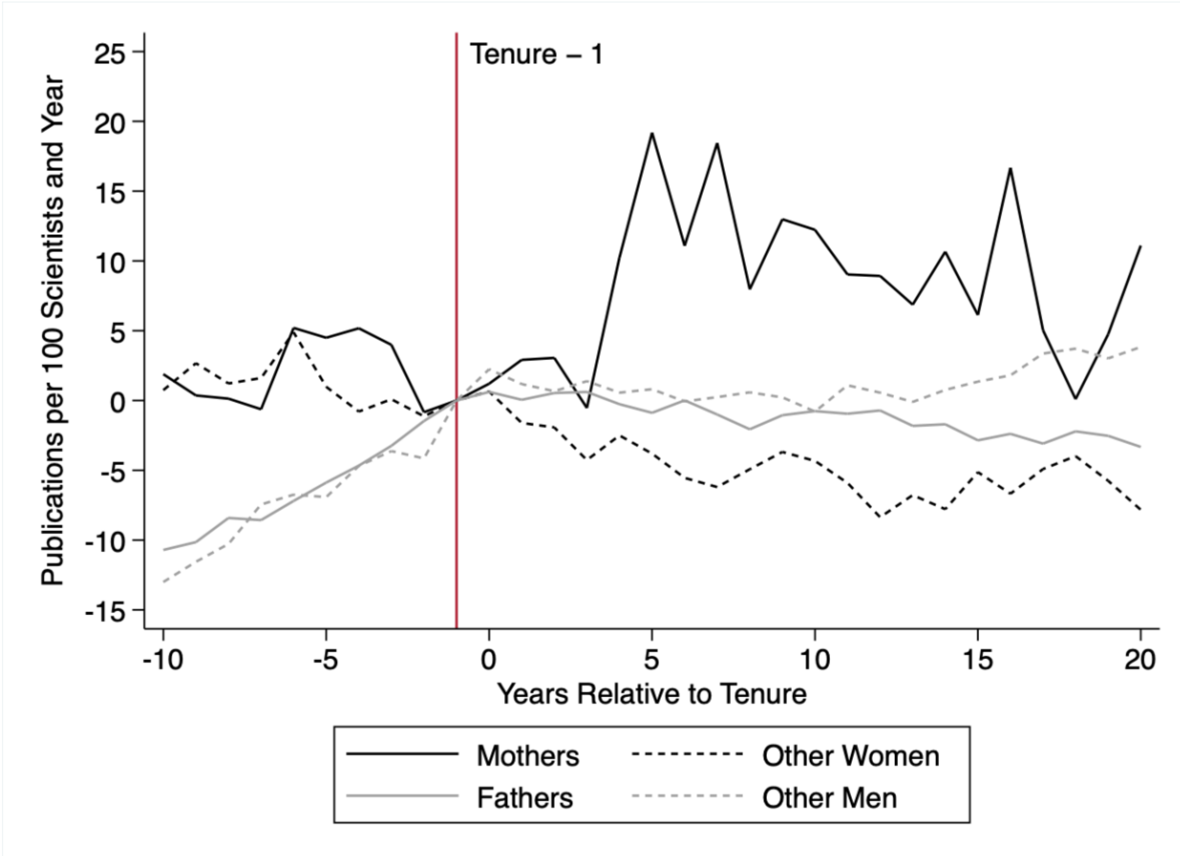


Notes: This figure plots the share of scientists in demographic group *d* who are promoted to the rank of associate or full professor within *t years to tenure* counting from the start year of their first assistant professor job. Data include 18,793 scientists in STEM who attain the rank of assistant professor; 12,757 are fathers, 4,787 other men, 207 mothers, and 1,042 other women.

FIGURE 5 – EVENT STUDY OF CHANGES IN THE PROBABILITY OF TENURE AFTER MARRIAGE

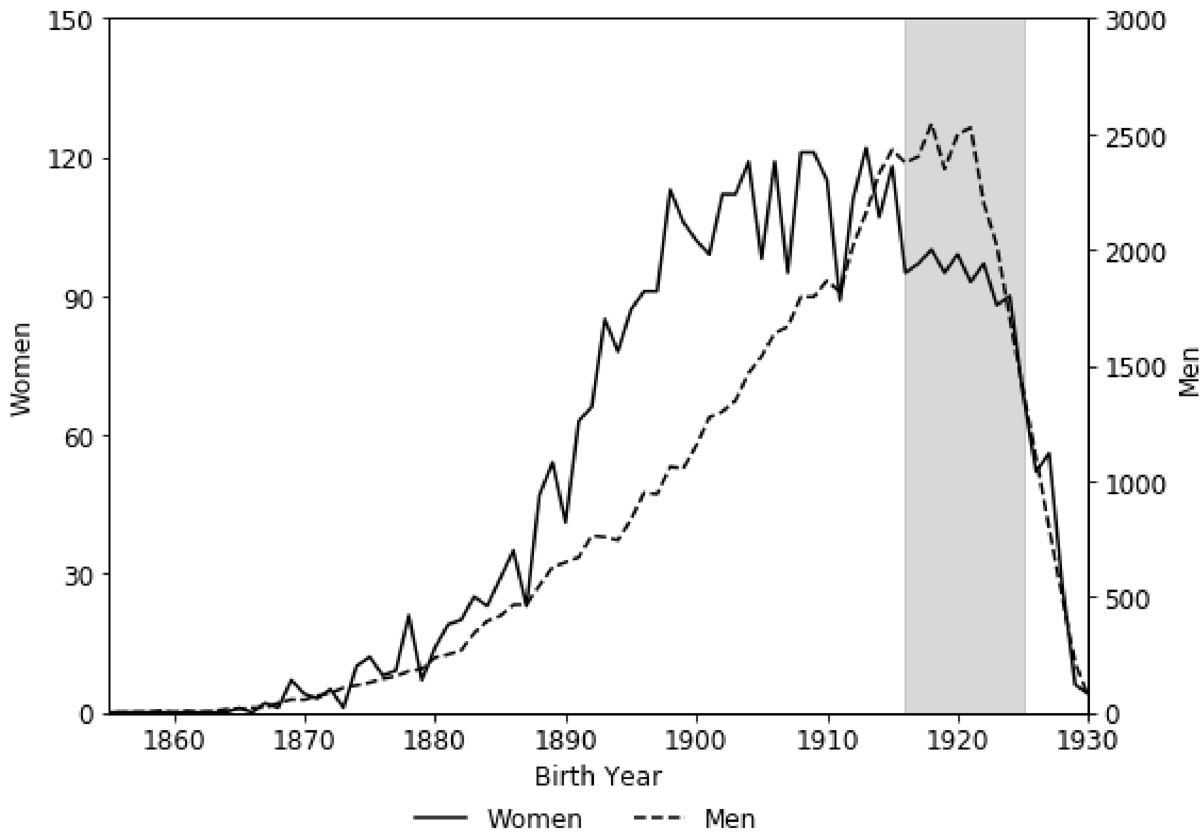
Notes: OLS estimates of β_s^d for demographic d (mothers, fathers, other married women, and other married men) in the equation $y_{is}^d = \beta_s^d EventTime_i + \delta_t + \alpha_a + \mu_f + \epsilon_{it}$ where y_{is}^d equals 1 if scientist i of demographic d holds a tenured job at the rank of associate or full professor in year *s* relative to marriage. The coefficient β_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 someone from the same demographic group one year before marriage. δ_t are publication year fixed effects; α_a are age fixed effects, and μ_f are field fixed effects. Data include 14,931 married scientists in any field (including STEM, as well as the biological and social sciences) who attain the rank of assistant professor; 12,175 of them are fathers, 2,370 other married men, 194 mothers, and 192 other married women.

FIGURE 6 – EVENT STUDIES OF CHANGES IN PUBLICATIONS PER YEAR AFTER TENURE



Notes: OLS estimates of β_s^d for demographic d (mothers, fathers, other women, and other men) in the equation $y_{is}^d = \beta_s^d EventTime_i + \delta_t + \alpha_a + \mu_f + \epsilon_{it}$ where y_{is}^d is the number of publications per scientist i (divided by the number of authors per publication, multiplied by 100) of demographic d in year relative to tenure s. Productivity is measured by publications in event year s after tenure per 100 scientists in demographic group d in year t of the publication. The coefficient β_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 they received tenure. δ_t are publication year fixed effects to capture variation in publishing intensity over time (e.g., as a result of variation in research funding); α_a are age fixed effects to control for variation in publishing across the life cycle of scientists. Field year fixed effects μ_f control for variation in the publishing intensity across fields f. Data include 25,019 scientists who become associate or full professors; 17,280 are fathers, 6,265 other men without children, 202 mothers, and 1,272 other women without children.

FIGURE 7 – WOMEN AND MEN ACTIVE IN AMERICAN SCIENCE IN 1956, BY BIRTH YEAR



Notes: Women and men who were active in American science in 1956, counted by their year of birth. Data include 70,230 American scientists born between 1850 and 1940; among them 4,032 are women and 66,198 are men. 22,934 of these scientists were in their 20s at the start of the baby boom; we have marked these cohorts (born between 1916 and 1925) in light grey. They include 923 women and 22,011 men.

Appendix A: Identifying Female Scientists

We tested and compared four alternative approaches to identify female scientists based on their names and their enrollment in a women's college:

1) *Manual Assignment*

   Specifically, we asked the data typists who hand-entered our data from the hard copies of the MoS (1921 and 1956) to flag names of female scientist. Data typists identified 2,674 of 82,094 American scientists (3.3 percent) in 1956 as women and 79,420 (96.7 percent) as men.

2) *Attendance at a Women's College*

   To create this measure, we assume that every who earned a degree at a women's college (in a time when the college only admitted women) was a woman.

   a. First, we collected a historical list of women's colleges throughout the United States

   b. Then we collected information on the first year in which these colleges admitted men or merged with other coeducational universities

   c. We use this information to create an indicator for *WoSCollege* which equals 1 for scientists who earned a degree at a women's college before it admitted men.

3) *Gender of Names in the US Census of 1940*

   Our third measure uses historical name frequencies of male and female names in the Census of 1940. Specifically, we assign a scientist to be female if 90 percent or more of people with the same first name in 1940 were women. Using a 90 percent cut-off points yields a distribution of women across birth cohorts that is similar to the distribution based on the manual assignment of names and the attendance at a women's college.

4) *Gender of Names in the Social Security Administration Data, 1880-2011*

   The fourth, and preferred measure of gender takes advantage of the universe of gender assignments in the records of the US Social Security Administration between 1880 and 2011. According to this variable, 4,412 of 82,094 American scientists in 1956 were women. This last variable was implemented by R's "gender" package.

TABLE A1 – INTENSITY ESTIMATES: EFFECTS OF ADDITIONAL CHILDREN ON PRODUCTIVITY IN PATENTS

	Patents					
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-5.870***	-5.628***	-5.245***	-2.432***	-2.504***	-2.189***
	(0.173)	(0.174)	(0.156)	(0.067)	(0.067)	(0.061)
1 Child	1.669***	1.822***	1.558***	1.095***	1.003***	0.991***
	(0.185)	(0.186)	(0.171)	(0.098)	(0.097)	(0.090)
2 Children	1.838***	1.950***	1.717***	1.232***	1.140***	1.123***
	(0.160)	(0.165)	(0.149)	(0.083)	(0.083)	(0.077)
3+ Children	1.781***	1.886***	1.712***	1.195***	1.109***	1.117***
	(0.168)	(0.166)	(0.157)	(0.086)	(0.085)	(0.079)
Female*1 Child	-2.284***	-2.589***	-2.664***	-1.234***	-1.201***	-1.281***
	(0.374)	(0.386)	(0.347)	(0.139)	(0.140)	(0.128)
Female*2 Children	0.535	0.490	0.127	-0.639***	-0.560**	-0.680***
	(0.763)	(0.761)	(0.730)	(0.233)	(0.232)	(0.218)
Female*3+ Children	-1.316***	-1.582***	-1.539***	-0.470***	-0.429***	-0.650***
	(0.331)	(0.349)	(0.306)	(0.120)	(0.123)	(0.111)
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	8.811	8.811	8.752	4.606	4.606	4.579

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

Notes: OLS estimates compare changes in the number of US patents by US scientists in STEM per year throughout 1930–1970. Column (1) estimates $y_{it} = \beta_1 Parent_i + \beta_2 x\ Child_i + \beta_3 Female * x\ Child_i + \delta_t + \pi_b + \mu_f + \epsilon_{it}$, where the dependent variable y_{it} counts US patents per scientist i (multiplied by 100) in year *t*. The variable $x\ Child_i$ indicates scientists who were parents with *x* number of children in 1956, $Female_i$ indicates scientists who are women, and $Female * x\ Child_i$ indicates scientists who are mothers with *x* number of children; δ_t are year fixed effects for years *t*, π_b are birth cohort fixed effects for birth years *b*, and μ_f are field fixed effects for fields *f*. Column (2) replaces birth cohort fixed effects from Column (1) with age fixed effects. Column (3) extends Column (1)'s estimates to scientists who in ages 18-80. Columns (4)-(6) include scientists across all disciplines respectively.

TABLE A2 – INTENSITY ESTIMATES: EFFECTS OF ADDITIONAL CHILDREN ON PRODUCTIVITY IN PUBLICATIONS

	Publications (1-6)						Citations (7-8)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-8.355***	-8.644***	-8.176***	-9.954***	-9.947***	-9.610***	-3.799**	-4.193*
	(0.258)	(0.256)	(0.235)	(0.197)	(0.196)	(0.181)	(1.886)	(2.253)
1 Child	0.910***	0.614***	0.994***	-0.292*	-0.223	-0.241	15.868*	15.630*
	(0.224)	(0.223)	(0.210)	(0.164)	(0.163)	(0.154)	(8.448)	(8.561)
2 Children	0.850***	0.270*	1.010***	0.466***	0.181	0.604***	12.723*	13.218**
	(0.157)	(0.151)	(0.150)	(0.128)	(0.126)	(0.122)	(6.734)	(6.627)
3+ Children	1.341***	0.682***	1.471***	2.070***	1.656***	2.295***	10.973**	11.561*
	(0.166)	(0.160)	(0.158)	(0.142)	(0.138)	(0.134)	(5.569)	(5.926)
Female*1 Child	2.157***	2.369***	2.611***	0.923*	0.757	0.973**	-13.510*	-14.250
	(0.797)	(0.793)	(0.784)	(0.516)	(0.515)	(0.491)	(7.564)	(8.821)
Female*2 Children	-2.175***	-1.945***	-2.301***	0.397	0.407	0.229	-12.451*	-13.293*
	(0.599)	(0.592)	(0.569)	(0.725)	(0.724)	(0.682)	(6.702)	(7.103)
Female*3+ Children	-5.378***	-5.045***	-5.339***	-2.623***	-2.472***	-2.698***	-9.138	-15.509*
	(0.870)	(0.863)	(0.821)	(0.621)	(0.617)	(0.597)	(8.284)	(8.839)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Birth Year FE	Yes	No	Yes	Yes	No	Yes	Yes	No
Age FE	No	Yes	No	No	Yes	No	No	Yes
Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Disciplines	STEM	STEM	STEM	All	All	All	STEM	STEM
Scientists' age	18-65	18-65	18-80	18-65	18-65	18-80	18-65	18-65
N (scientists x years)	1,204,592	1,204,592	1,298,053	2,391,179	2,391,179	2,591,524	1,204,592	1,204,592
Pre-baby boom mean	11.189	11.189	11.208	15.832	15.832	15.862	21.275	21.275

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

Notes: OLS estimates compare changes in the number of publications by US scientists in STEM per year throughout 1930–1970. Column (1) estimates $y_{it} = \beta_1 Parent_i + \beta_2 x\ Child_i + \beta_3 Female * x\ Child_i + \delta_t + \pi_b + \mu_f + \epsilon_{it}$, where the dependent variable y_{it} counts US patents per scientist i (divided by the number of authors per publication, multiplied by 100) in year t. Variables $x\ Child_i$, $Female_i$, and $Female * x\ Child_i$ are identical to the same variables in Table A1; δ_t are year fixed effects for years t, π_b are birth cohort fixed effects for birth years b, and μ_f are field fixed effects for fields *f*. Column (2) replaces birth cohort fixed effects from Column (1) with age fixed effects. Column (3) extends Column (1)'s estimates to scientists who in ages 18-80. Columns (4)-(6) include scientists across all disciplines respectively. Columns (7)-(8) replicate columns (1)-(2) using citations per scientist *I* in year *t*.

TABLE A3 – PRODUCTIVITY MEASURED BY INVENTOR-WEIGHTED PATENTS

	Patents per 100 scientists per year					
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-5.245***	-5.058***	-4.686***	-2.184***	-2.253***	-1.966***
	(0.150)	(0.151)	(0.135)	(0.059)	(0.059)	(0.054)
Parent	1.601***	1.635***	1.512***	1.055***	0.953***	0.968***
	(0.122)	(0.125)	(0.113)	(0.061)	(0.061)	(0.057)
Female*Parent	-0.669*	-0.802**	-1.013***	-0.682***	-0.629***	-0.754***
	(0.369)	(0.371)	(0.347)	(0.117)	(0.117)	(0.109)
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	7.955	7.955	7.903	4.151	4.151	4.127

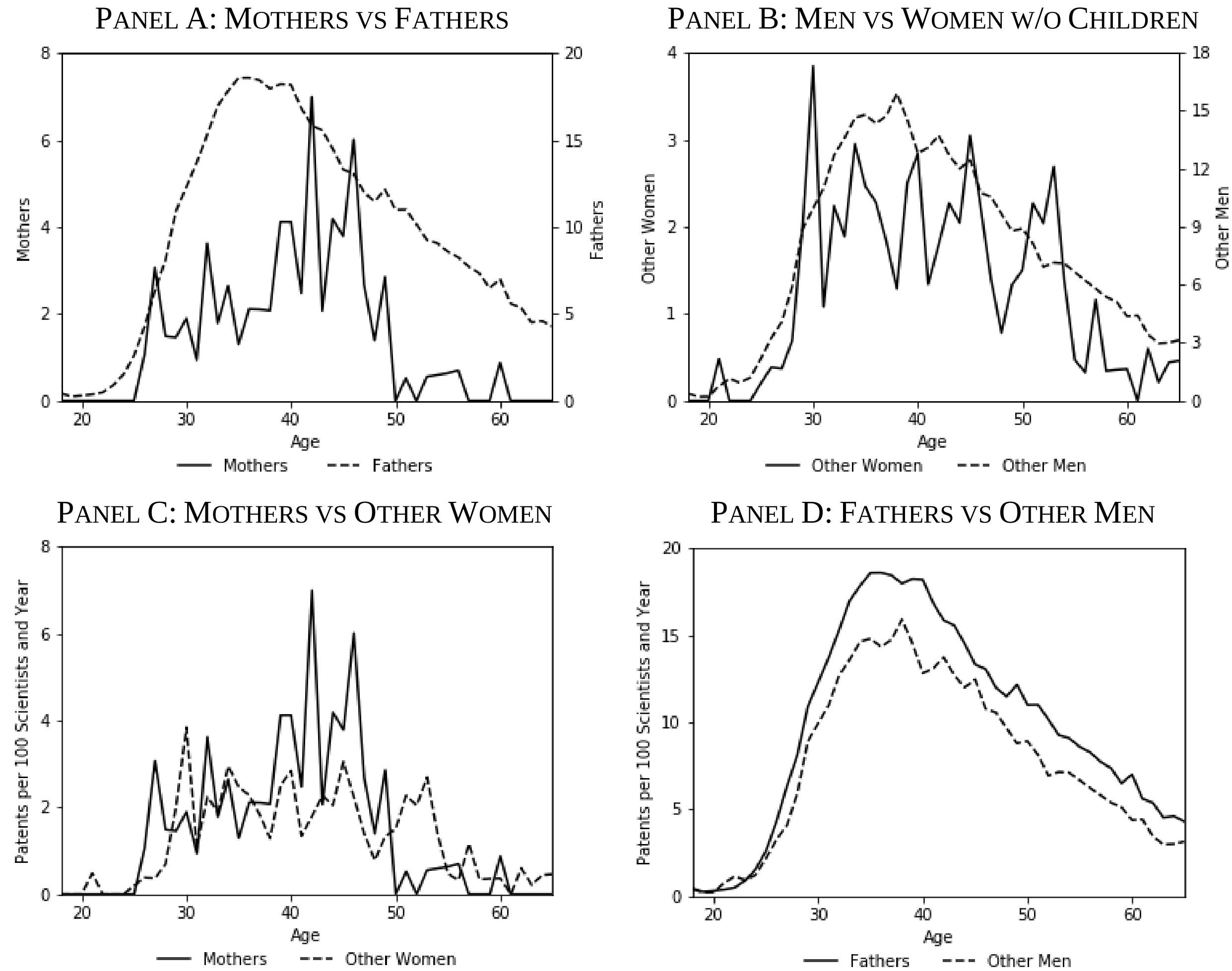
*** denotes significance at the 1-percent level, ** at the 5-percent level, and * at the 10-percent level

Notes: OLS estimates compare changes in the number of US patents by US scientists per year between 1930 and 1970. Column (1) estimates $y_{it} = \beta_1 Parent_i + \beta_2 Female_i + \beta_3 Female * Parent_i + \delta_t + \pi_b + \mu_f + \epsilon_{it}$, where the dependent variable y_{it} counts US patents per scientist i (divided by the number of MoS inventors per patent, multiplied by 100) in year *t*. The variable $Parent_i$ indicates scientists who were parents in 1956, $Female_i$ is an indicator for women, and $Female * Parent_i$ identifies mothers; δ_t are year fixed effects for years t, π_b are birth cohort fixed effects for birth years b, and μ_f are field fixed effects for fields *f*. Robust standard errors in parenthesis. Columns (1-3) estimate regressions for the physical sciences (STEM, including physics, mathematics, and engineering), Column (2) includes age fixed effects (and excludes cohort fixed effects). Column (3) extends the data to include older scientists up to age 80. Columns (4)-(6) include scientists across all disciplines respectively.

FIGURE A1 – US BIRTHS PER 1,000 PEOPLE FROM 1930 TO 1970

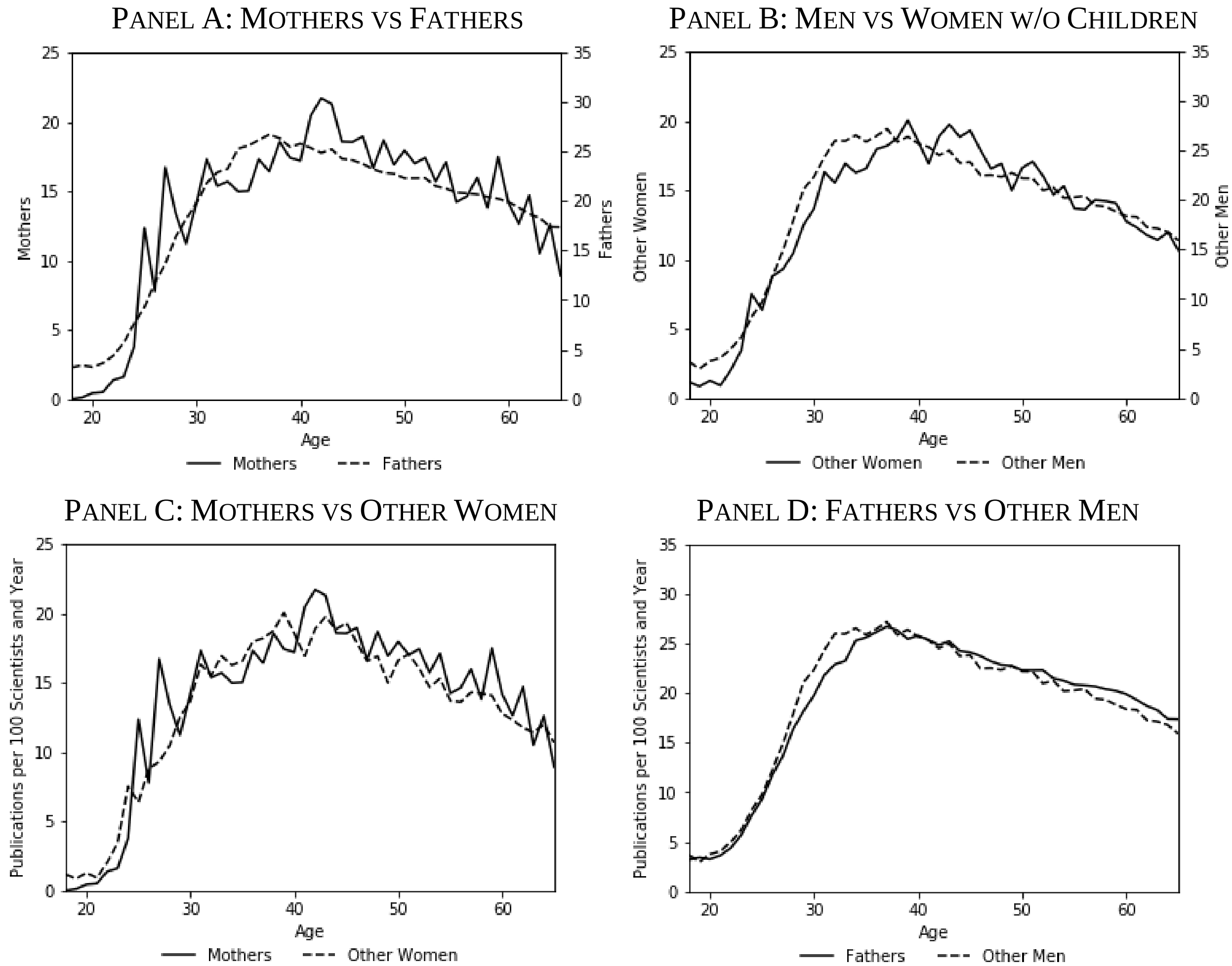
Notes: US births per 1,000 people from the Centers for Disease Control and Prevention (2003). Birth years in grey mark the official period of the baby boom, as defined by the US Census.

FIGURE A2 – PRODUCTIVITY CHANGES IN PATENTING ACROSS THE LIFE CYCLE OF SCIENTISTS



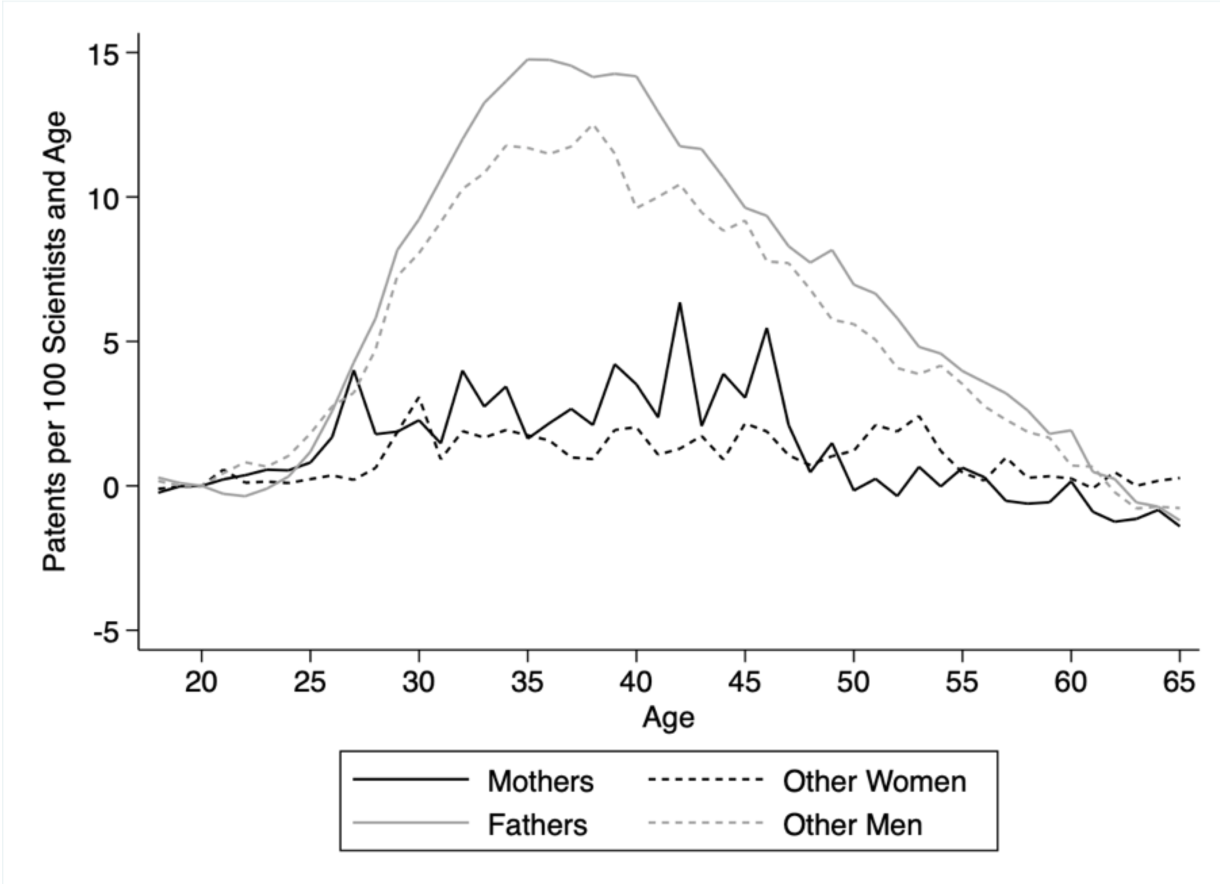
Notes: Panel A: 97,608 patents by 26,081 American scientists in STEM, including 25,829 men and 252 women, who were active in US science in 1956 and had at least one child. *Panel B:* 23,713 patents by 9,287 American scientists in STEM, including 8,367 men and 920 women, who were active in US science in 1956 and were not parents. *Panel C:* 589 patents by 1,172 female American scientists in STEM, including 252 mothers and 920 women without children, who were active in US science in 1956 and whose gender and birth years are known. *Panel D:* 120,732 patents by 34,196 male American scientists in STEM, including 25,829 fathers and 8,367 men without children, who were active in US science in 1956 and whose gender and birth years are known.

FIGURE A3 – PRODUCTIVITY CHANGES IN PUBLISHING ACROSS THE LIFE CYCLE OF SCIENTISTS



Notes: Panel A: 342,151.14 author-weighted publications by 49,879 American scientists in all disciplines, including 48,987 men and 892 women, who were active in US science in 1956 and had at least one child. *Panel B:* 127,229.04 author-weighted publications by 20,351 American scientists in all disciplines, including 17,211 men and 3,140 women, who were active in US science in 1956 and were not parents. *Panel C:* 19,743.69 author-weighted publications by 4,032 female American scientists in all disciplines, including 892 mothers and 3,140 women without children, who were active in US science in 1956 and whose gender and birth years are known. *Panel D:* 449,636.50 author-weighted publications by 66,198 male American scientists in all disciplines, including 48,987 fathers and 17,211 men without children, who were active in US science in 1956 and whose gender and birth years are known.

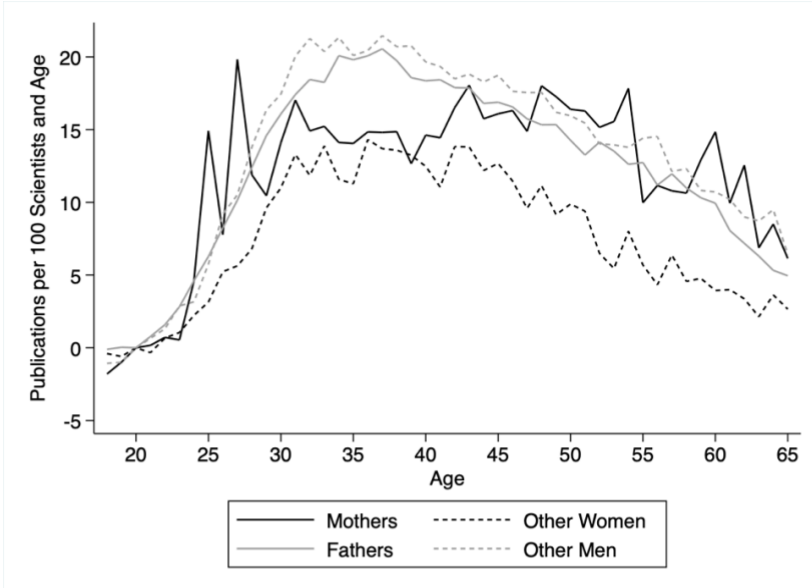
FIGURE A4 – AGE-VARYING ESTIMATES OF PRODUCTIVITY, INVENTOR-WEIGHTED PATENTS



Notes: OLS estimates of β_a^d for demographic d (mothers, fathers, other women, and other men) in the equation $y_{ia}^d = \beta_a^d Age_i + \delta_t + \pi_y + \mu_f + \epsilon_{it}$ where y_{ia}^d are US patents per 100 scientists of demographic d in age a. To account for co-authorships, we divide co-authored patents by the number of MoS inventors. The coefficient β_a^d is a vector of age-varying estimates of inventions created by 100 scientists of age a and demographic d compared with scientists in the same demographic at age 20. δ_t are patent application year fixed effects to capture variation in patenting over time; π_y are fixed effects for birth years y to control for variation in productivity across cohorts. Field fixed effects μ_f control for variation in patenting across fields. Data include 35,368 STEM scientists who were active in American science in 1956; 25,829 are fathers, 8,367 other men without children, 252 mothers, and 920 other women without children.

FIGURE A5 – AGE-VARYING ESTIMATES OF PRODUCTIVITY MEASURED BY PUBLICATIONS

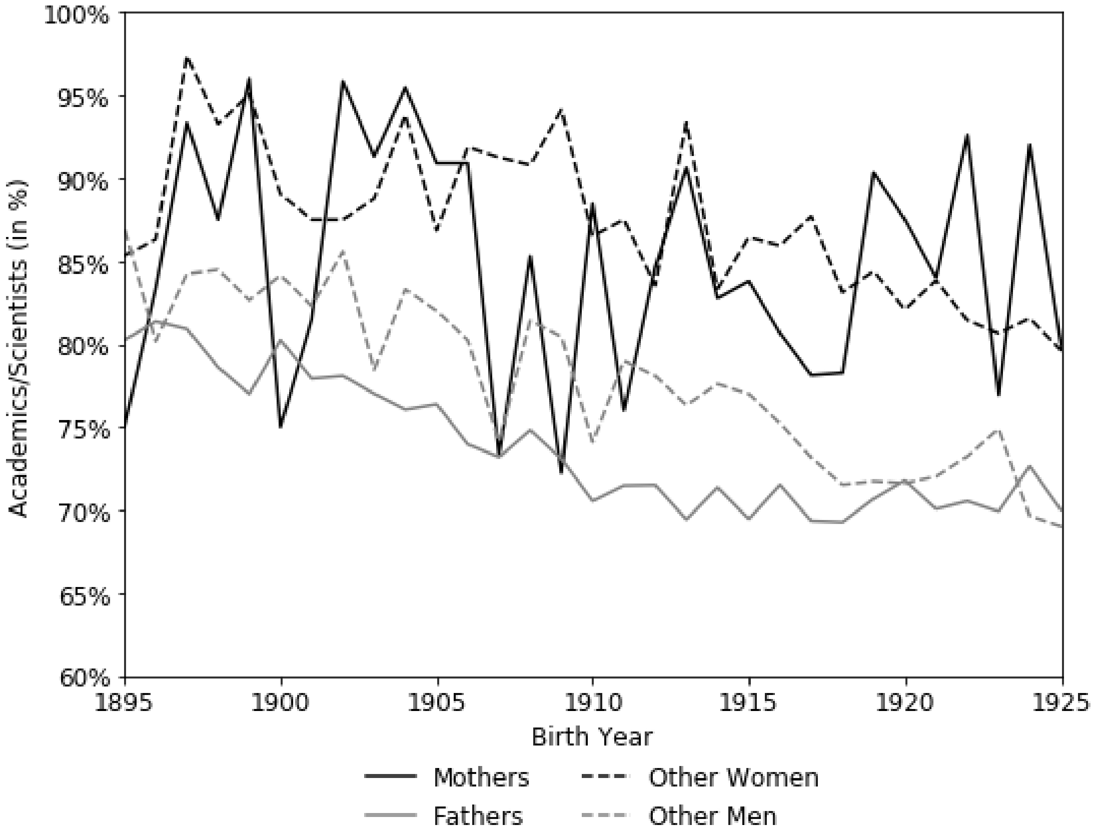
PANEL A: ACADEMICS WITHOUT TENURE



PANEL B: ACADEMICS WITH TENURE

Notes: OLS estimates of β_a^d for demographic d (mothers, fathers, other women, and other men) in the equation $y_{ia}^d = \beta_a^d Age_i + \delta_t + \pi_y + \mu_f + \epsilon_{it}$ where variables y_{ia}^d, β_a^d, δ_t, π_y, and μ_f are identical to those in Figure 1. *Panel A:* Academics who were not associate or full professors in all disciplines, including a total of 45,211 scientists; 31,707 are fathers, 10,946 other men without children, 690 mothers, and 1,868 other women without children. *Panel B:* Associate and full professors in all disciplines, including a total of 25,019 scientists; 17,280 are fathers, 6,265 other men without children, 202 mothers, and 1,272 other women without children.

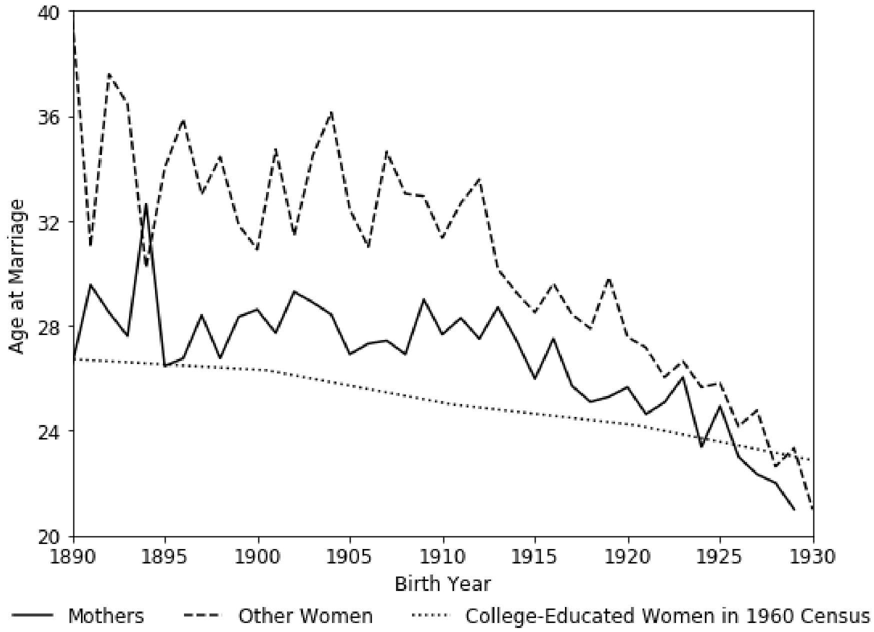
FIGURE A6 – PARTICIPATION IN ACADEMIA BY GENDER AND BIRTH YEAR



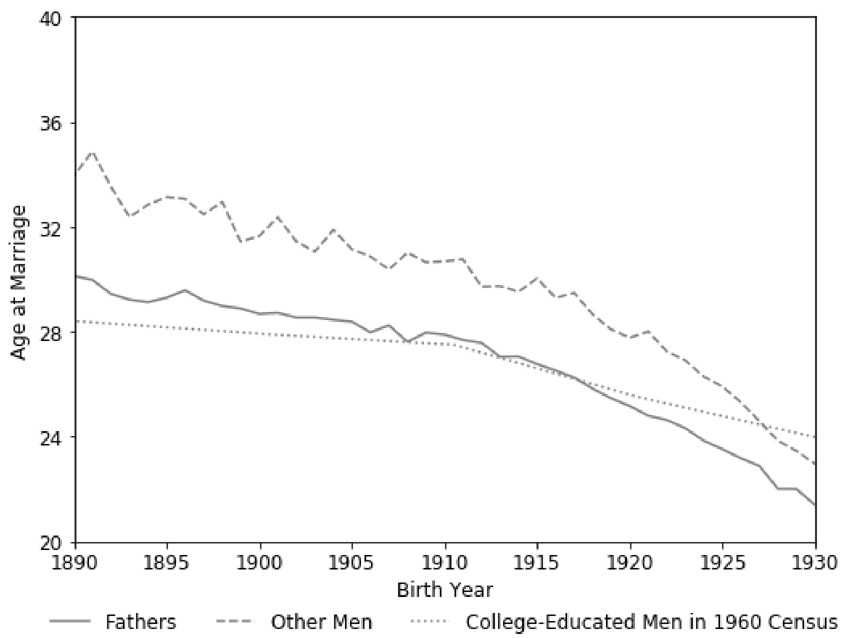
Notes: The share of scientists working in academia (measured by employment titles, including instructors, lecturers, professors) among all scientists. Data include 754 mothers, 2,783 other women, 36,140 fathers, and 13,269 other men who participated in academia and born between 1850 and 1940.

FIGURE A7 – MEAN AGE AT MARRIAGE BY BIRTH YEAR

PANEL A: WOMEN

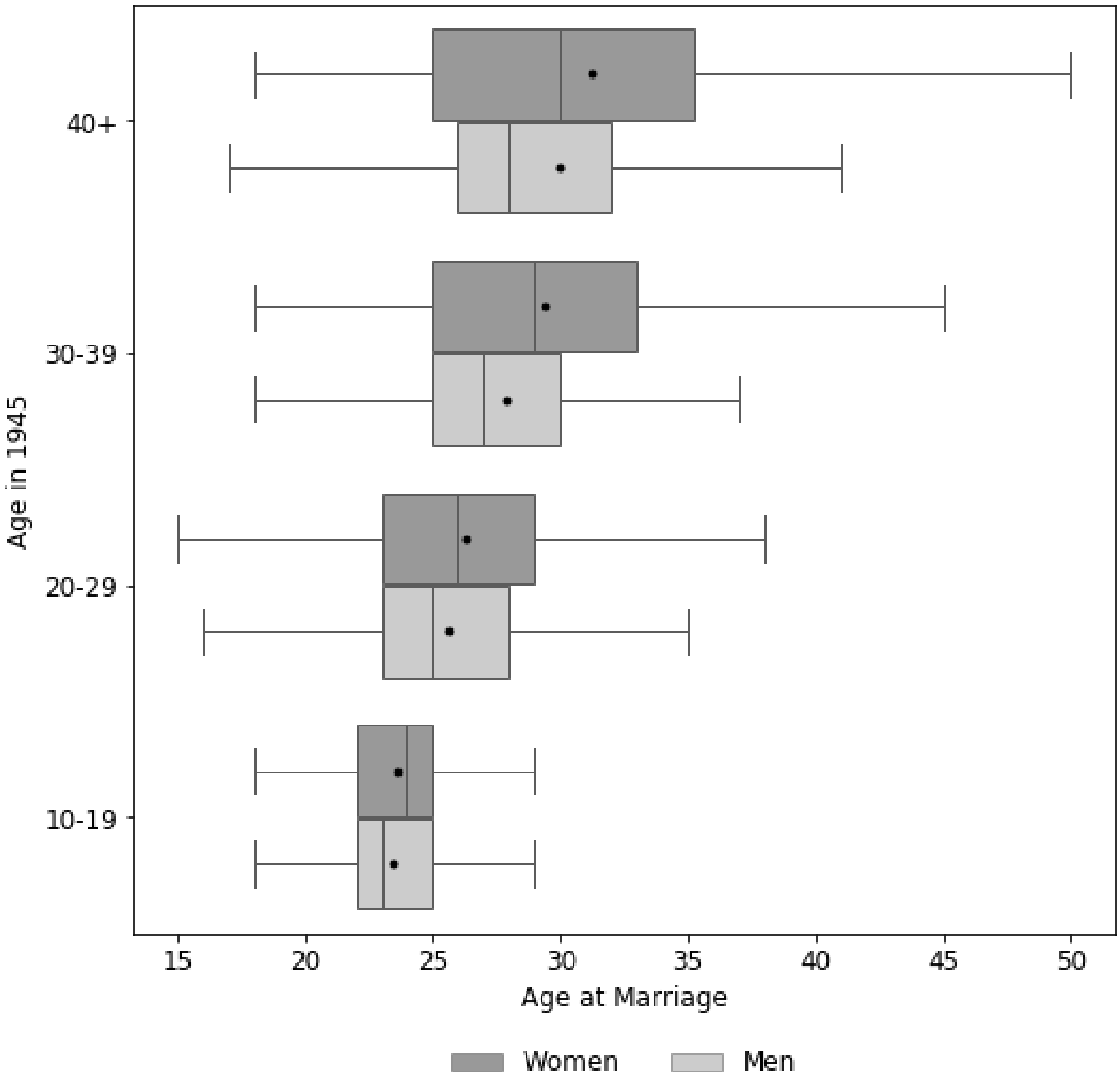


PANEL B: MEN



Notes: Panel A: Mean age at marriage for female scientists by parenthood, and birth year. We included median ages at marriage for college-educated women by birth year from the 1960 US Census. Data include 1,566 women, of which 832 are mothers and 734 are other women. *Panel B:* Mean age at marriage for male scientists by parenthood, and birth year. Data include 55,770 men, of which 46,837 are fathers, and 8,933 are other men. We included median ages at marriage for college-educated men by birth year from the 1960 US Census.

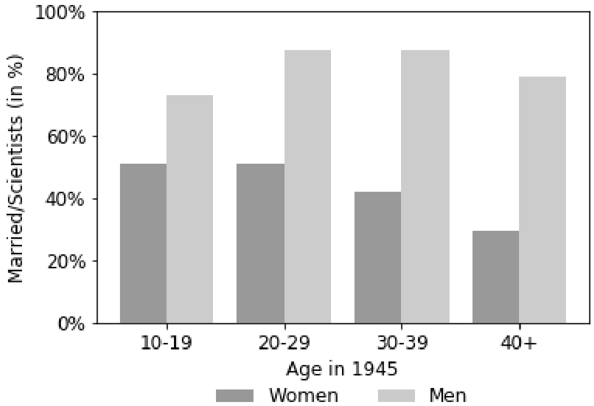
FIGURE A8 – AGE AT MARRIAGE BY BIRTH COHORT AND GENDER



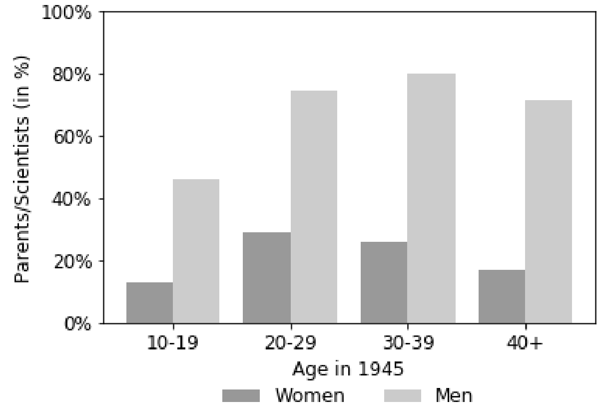
Notes: Mean and median ages at marriage for scientists across gender and birth cohorts. Birth cohorts are defined using the scientists' ages in 1945. We calculated each scientists age at marriage by subtracting their birth year from the year of their marriage. Both of these variables are reported in the MoS (1956). Data include 57,336 scientists who are married and whose gender and birth years are known, of which 1,566 are women and 55,770 are men.

Figure A9 – Selection into Marriage and Parenting

Panel A: Share of Married Scientists

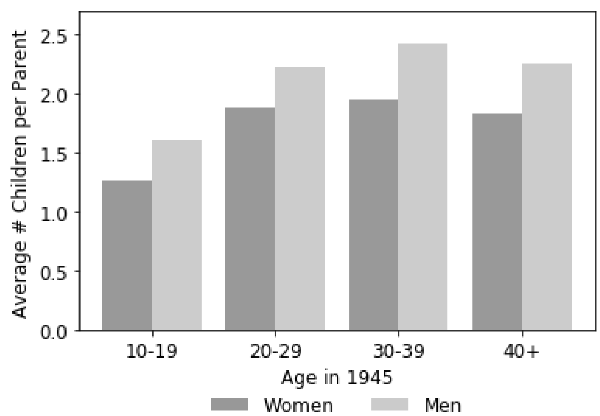


Panel B: Share of Parents



Panel C: Number of Children per Scientist

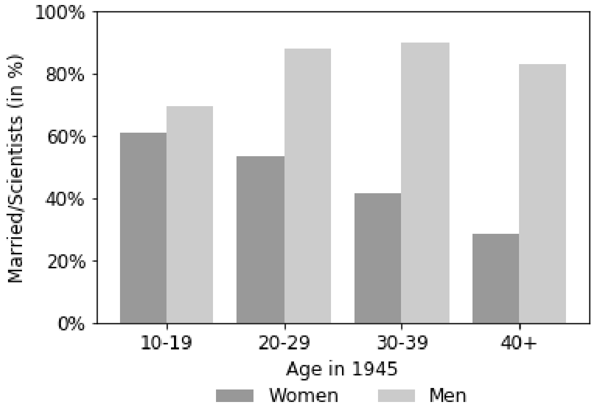
Panel D: Number of Children per Parent



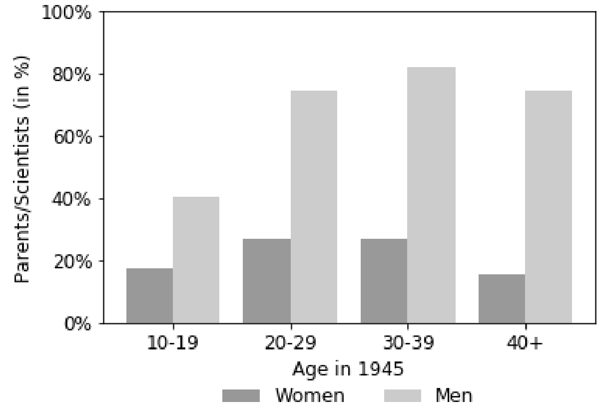
Notes: To investigate selection into marriage and parenting, we examine changes in the share of scientists who decided to marry and have children across birth cohorts, measured by their age in 1945, at the beginning of the baby boom (1946-1964). *Panel A* plots the share of scientists who were married. *Panel B* plots the share of scientists (in %) who report having one or more children in 1956. Data for Panel A and B include 70,230 scientists who were active in American science in 1956 and whose gender and birth years are known; among them 4,032 are women and 66,198 are men. *Panel C:* Average number of children per scientist by birth cohorts. Data include 70,230 scientists whose gender and birth years are known, of which 4,032 are women and 66,198 are men. *Panel D:* Average number of children per scientist with at least one child by birth cohorts. Data for Panel D include 49,879 scientists who are parents; among them 892 are women and 48,987 are men.

FIGURE A10 – SELECTION INTO MARRIAGE AND PARENTING IN STEM

PANEL A: SHARE OF MARRIED SCIENTISTS

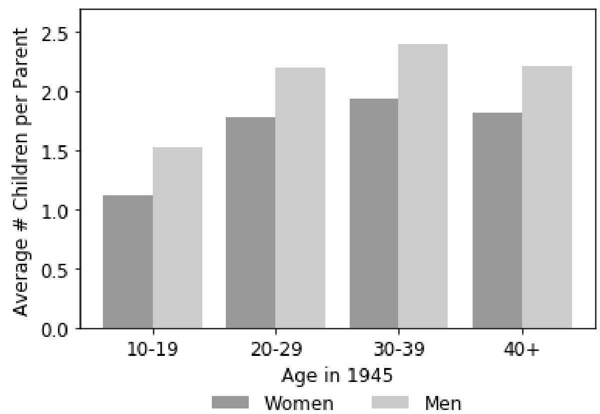


PANEL B: SHARE OF PARENTS



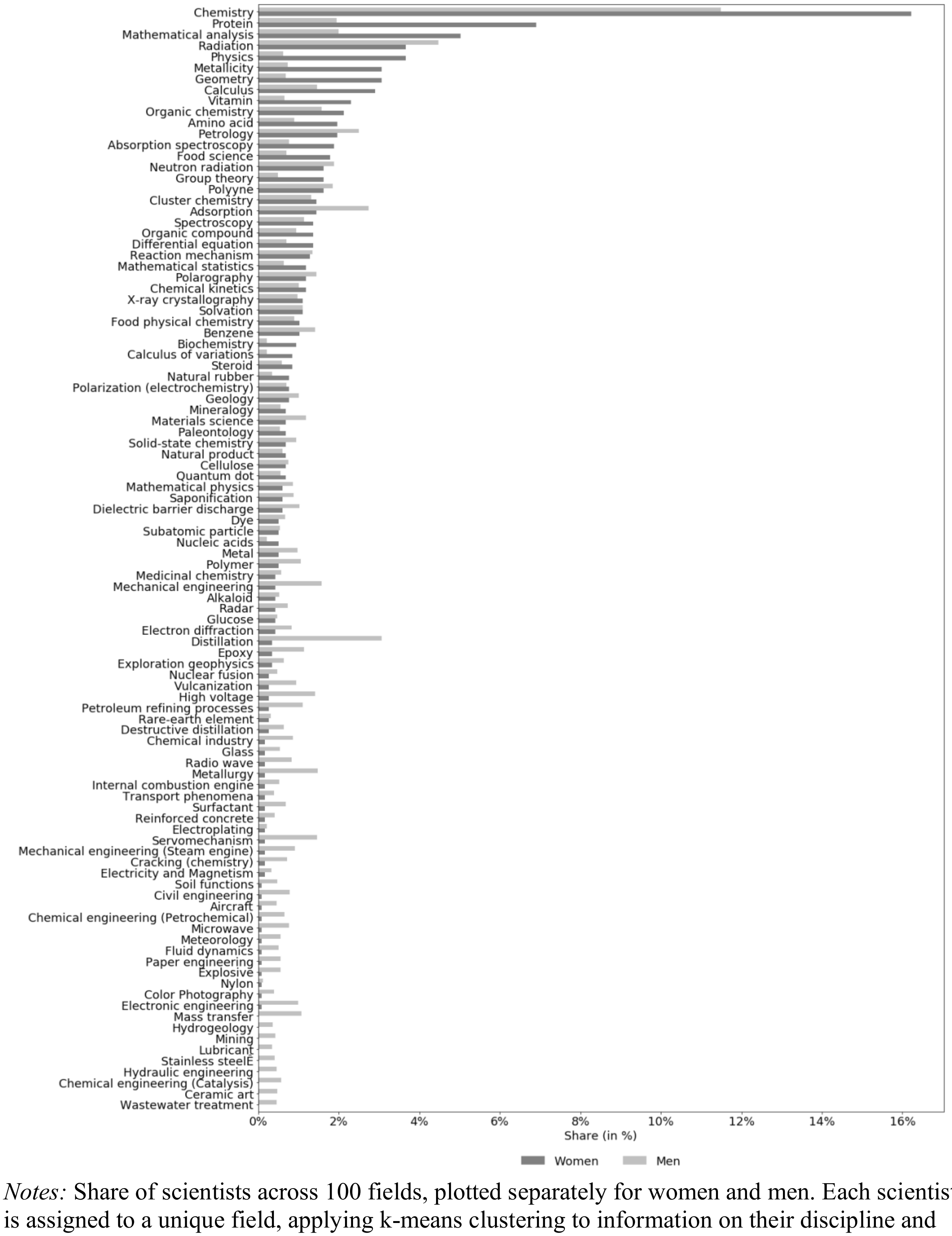
PANEL C: NUMBER OF CHILDREN PER SCIENTIST

PANEL D: NUMBER OF CHILDREN PER PARENT



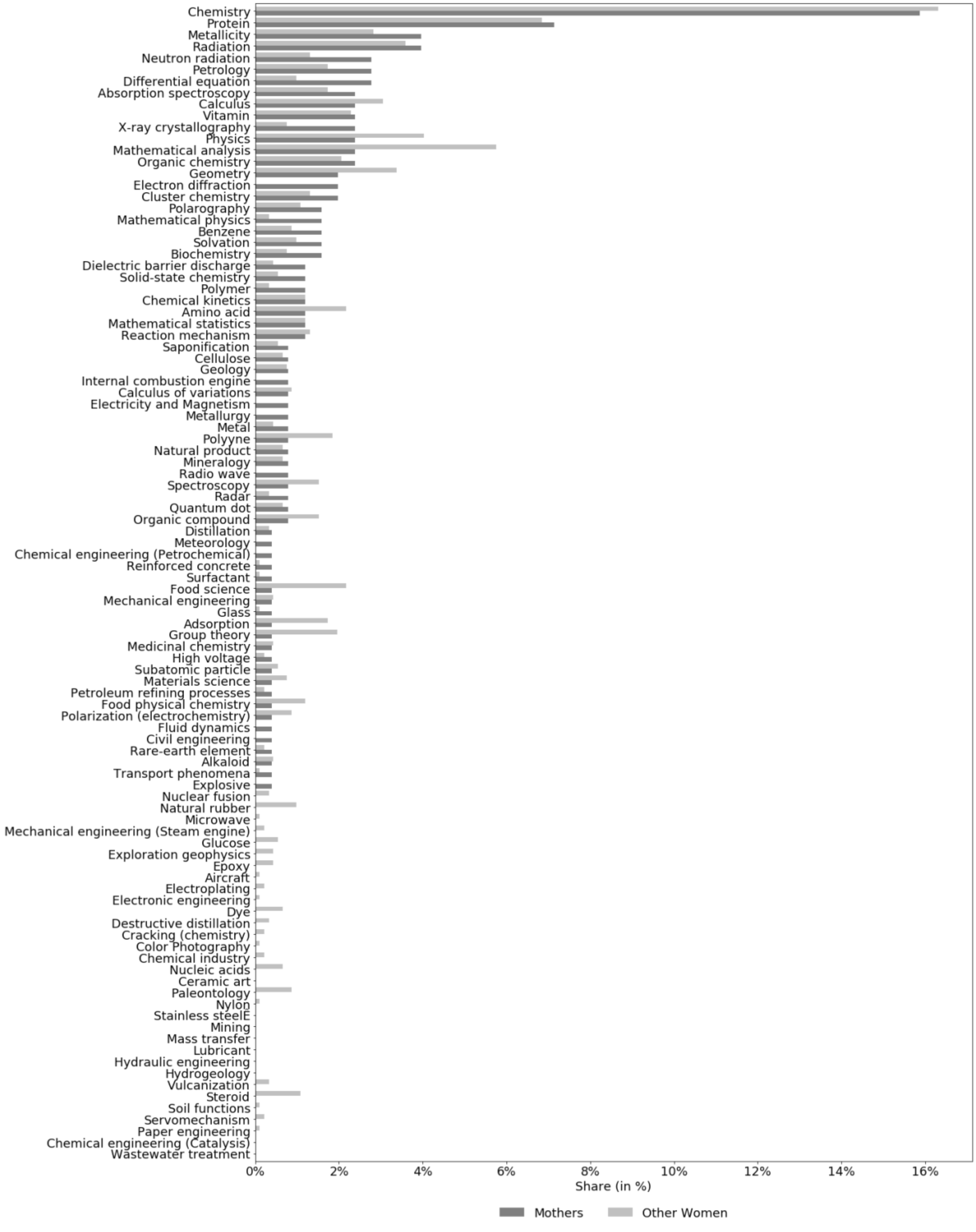
Notes: To investigate selection into marriage and parenting, we examine changes in the share of scientists who decided to marry and have children across birth cohorts, measured by their age in 1945, at the beginning of the baby boom (1946-1964). *Panel A* plots the share of scientists who were married. *Panel B* plots the share of scientists (in %) who report having one or more children in 1956. Data for Panel A and B include 35,368 scientists who were active in American science in 1956 and whose gender and birth years are known; among them 1,172 are women and 34,196 are men. *Panel C:* Average number of children per scientist by birth cohorts. Data include 35,368 scientists whose gender and birth years are known, of which 1,172 are women and 34,196 are men. *Panel D:* Average number of children per scientist with at least one child by birth cohorts. Data include 26,081 parents of which 141 are women and 25,829 are men.

FIGURE A11 – DISTRIBUTION OF SCIENTISTS ACROSS FIELDS: WOMEN VS MEN



Notes: Share of scientists across 100 fields, plotted separately for women and men. Each scientist is assigned to a unique field, applying k-means clustering to information on their discipline and research fields (implementing an approach from Moser and San 2020).

FIGURE A12 – DISTRIBUTION OF SCIENTISTS ACROSS FIELDS: MOTHERS VS OTHER WOMEN

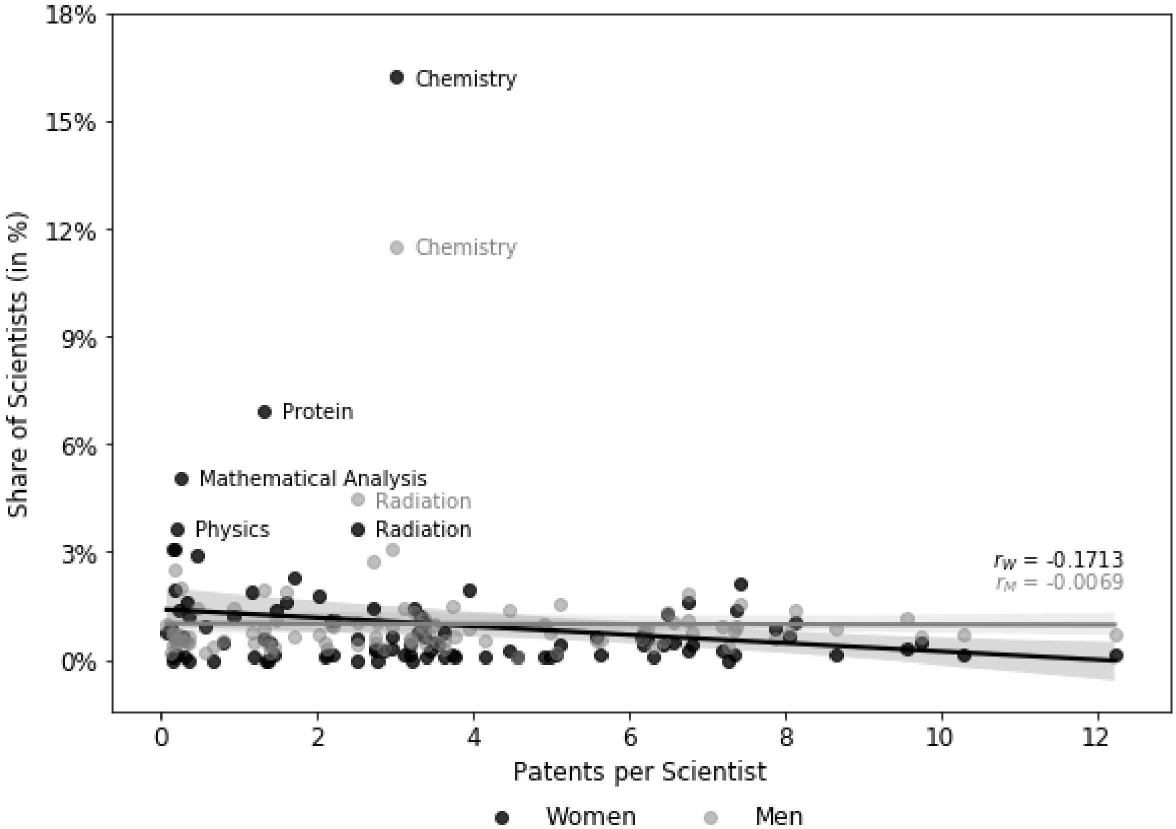


Notes: Share of female scientists across 100 fields, plotted separately for mothers and other women. Each scientist is assigned to a unique field, applying k-means clustering to information on their discipline and research fields (implementing an approach from Moser and San 2020).

FIGURE A13 – DISTRIBUTION OF SCIENTISTS ACROSS FIELDS: FATHERS VS OTHER MEN

Notes: Share of male scientists across 100 fields, plotted separately for fathers and other men. Each scientist is assigned to a unique field, applying k-means clustering to information on their discipline and research fields (implementing an approach from Moser and San 2020).

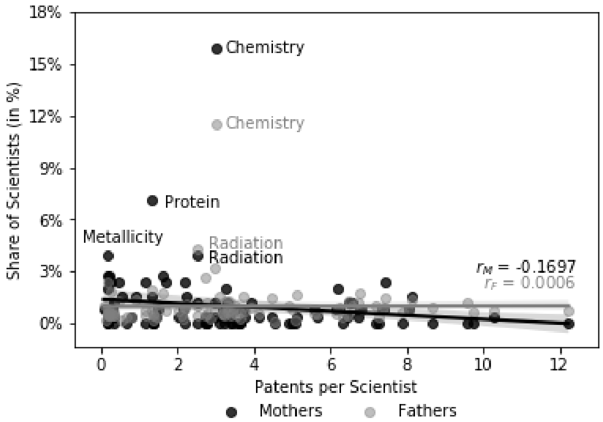
FIGURE A14 – FIELD DISTRIBUTION BY PRODUCTIVITY IN PATENTS AND GENDER



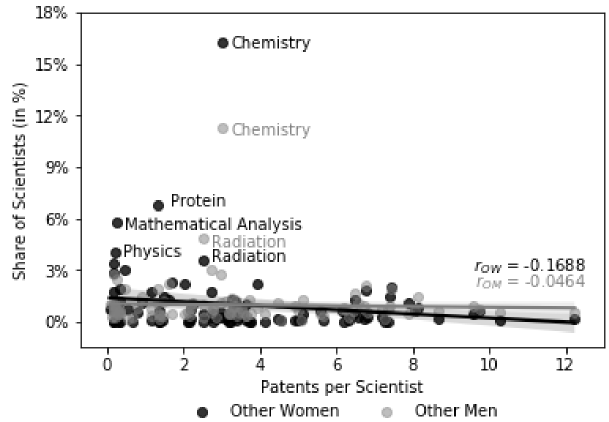
Notes: Share of scientists across 100 fields, plotted by patents per scientists per field and separately for women and men. Each scientist is assigned to a unique field, applying k-means clustering to information on their discipline and research fields (implementing an approach from Moser and San 2020).

FIGURE A15 – SELECTION INTO FIELDS: SHARE OF SCIENTISTS VS PATENTS PER SCIENTIST

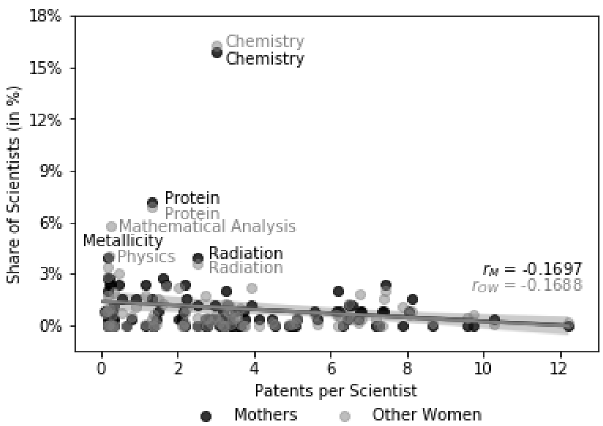
PANEL A: MOTHERS VS FATHERS



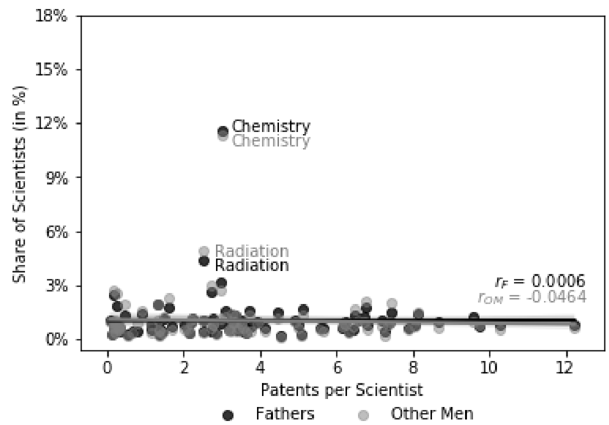
PANEL B: MEN VS WOMEN W/O CHILDREN



PANEL C: MOTHERS VS OTHER WOMEN

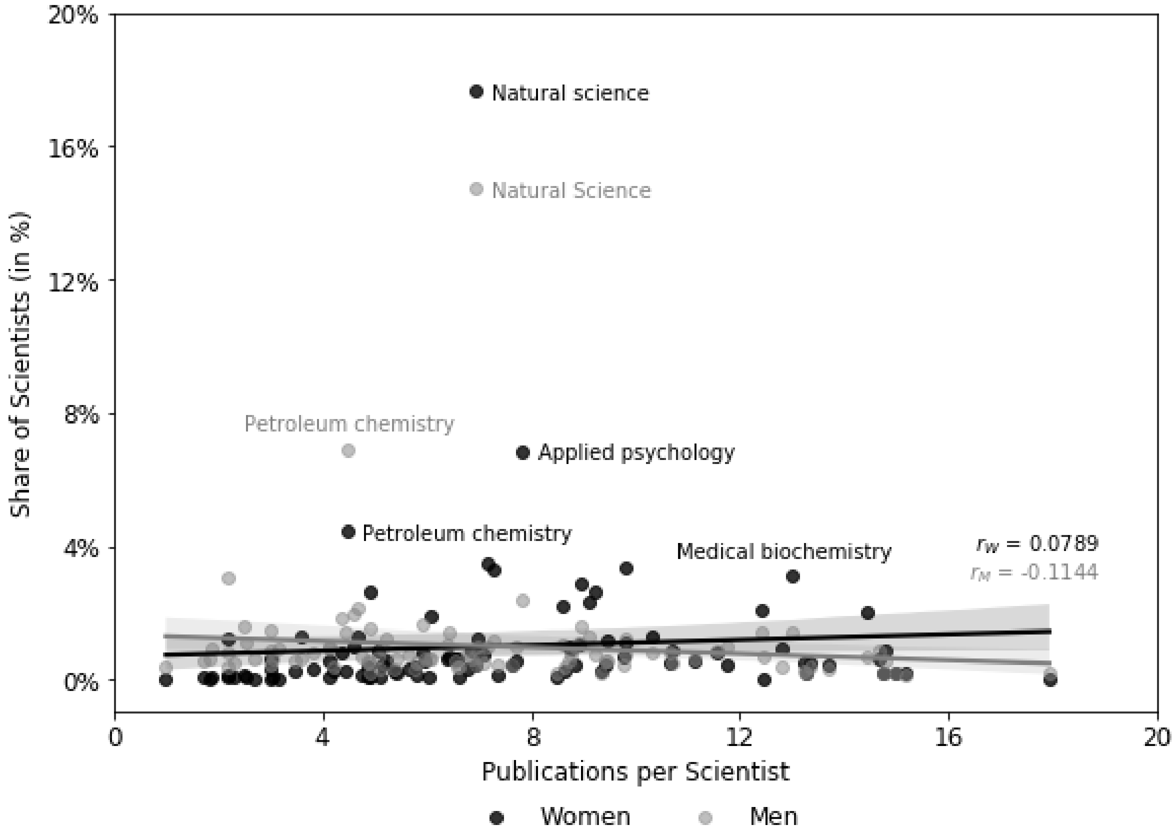


PANEL D: FATHERS VS OTHER MEN



Notes: Panel A: Share of scientists across 100 fields, plotted by patents per scientists per field and separately for mothers and fathers. *Panel B:* Share of scientists across 100 fields, plotted by patents per scientists per field and separately for women and men who were not parents. *Panel C:* Share of scientists across 100 fields, plotted by patents per scientists per field and separately for mothers and other women. *Panel D:* Share of scientists across 100 fields, plotted by patents per scientists per field and separately for fathers and other men.

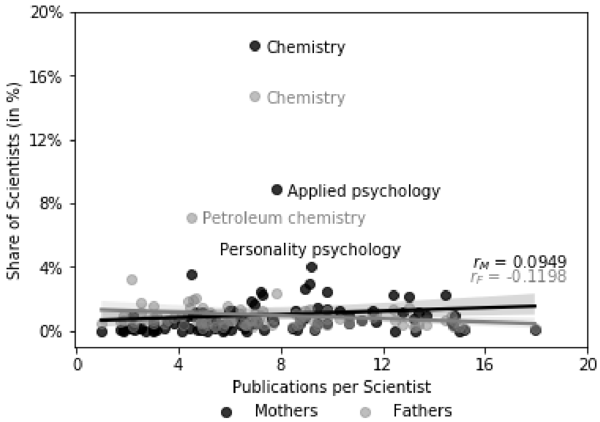
FIGURE A16 – FIELD DISTRIBUTION BY PRODUCTIVITY IN PUBLICATIONS AND GENDER



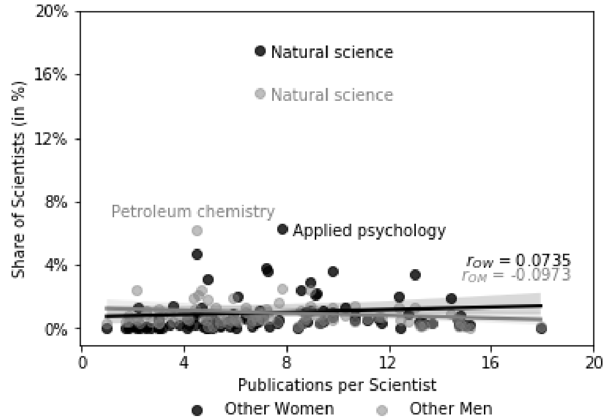
Notes: Share of scientists across 100 fields, plotted by publications per scientist per field and separately for women and men. Each scientist is assigned to a unique field, applying k-means clustering to information on their discipline and research fields (implementing an approach from Moser and San 2020).

FIGURE A17 – SELECTION INTO FIELDS: SHARE OF SCIENTISTS VS PUBLICATIONS PER SCIENTIST

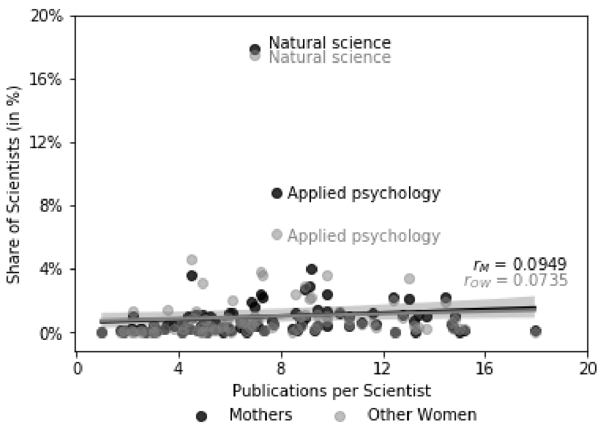
PANEL A: MOTHERS VS FATHERS



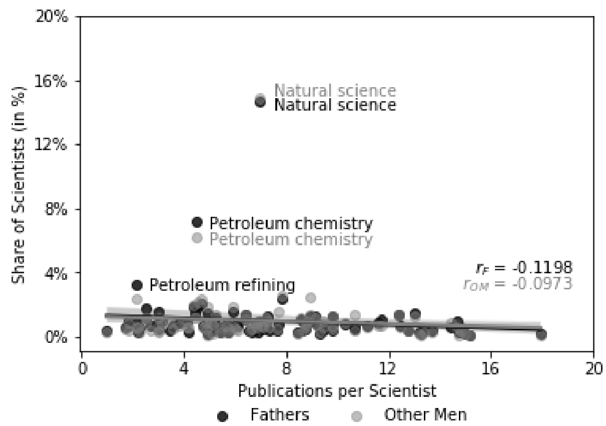
PANEL B: MEN VS WOMEN W/O CHILDREN



PANEL C: MOTHERS VS OTHER WOMEN



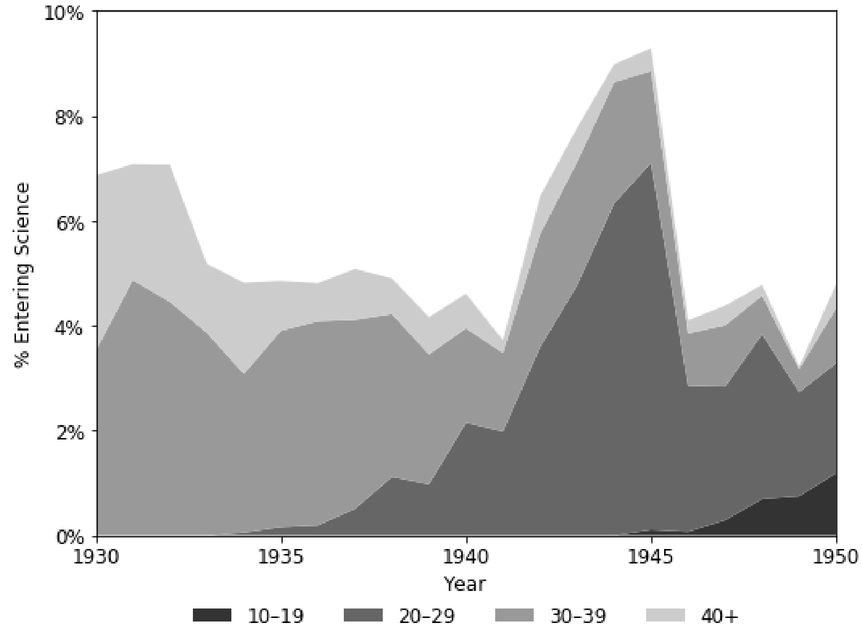
PANEL D: FATHERS VS OTHER MEN



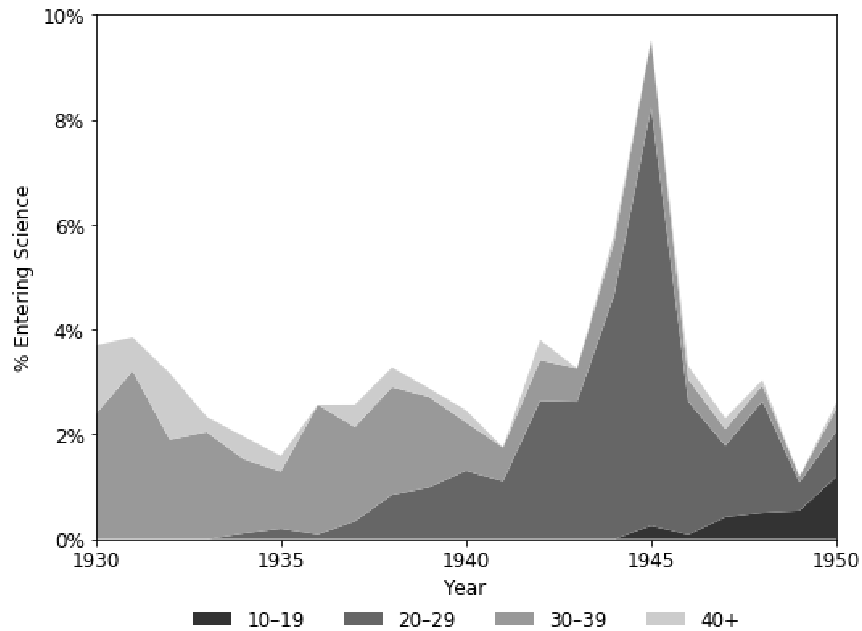
Notes: Panel A: Share of scientists across 100 fields, plotted by publications per scientist per field and separately for mothers and fathers. *Panel B:* Share of scientists across 100 fields, plotted by publications per scientist per field and separately for women and men who were not parents. *Panel C:* Share of scientists across 100 fields, plotted by publications per scientist per field and separately for mothers and other women. *Panel D:* Share of scientists across 100 fields, plotted by publications per scientist per field and separately for fathers and other men.

FIGURE A18 – SHARE OF WOMEN AMONG NEW SCIENTISTS ENTERING PER YEAR

PANEL A: ALL DISCIPLINES



PANEL B: PHYSICAL SCIENCES



Notes: Entry into US science measures the change in the number of women and men who were active in US science in a given year between 1930 and 1955. A scientist is defined to be "active" after the start year of her first university enrollment or first job, as described in section 2.1.3. Shades represent cohorts, separated by their age in 1945, and darker shades represent younger cohorts. For example, the cohort *20-29* references women aged 20 to 29 at the start of the baby boom in 1945 (adjusted for 9 months of pregnancy).