WOMEN IN SCIENCE
LESSONS FROM THE BABY BOOM

SCOTT KIM, WHARTON AND
PETRA MOSER, NYU, NBER, AND CEPR*

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How do children impact innovation and productivity in science? To answer this question, we examine detailed biographical data for 83,000 American scientists in 1956, at the height of the baby boom (1946-64). Using both patents and publications to measure productivity, we show that mothers have a unique pattern of productivity across the life cycle, reaching peak productivity in their early 40s, long after other scientists decline. Event studies of marriage reveal that mothers experience a large and persistent increase in output after the first 15 years of marriage, while other scientists begin to fade after the first 10 years of marriage. These differences in timing have important implications for gender inequality in science: mothers were 21 percent less likely to advance to tenure compared with fathers, and 19 percent less than other women. Analyses of selection yield no evidence that mothers were less productive than other women before marriage. However, female scientists, and especially mothers, were less likely to survive in science. Scientist-level employment data reveal a dramatic decline in participation by women who were of child-bearing age during the baby boom. These findings suggest that the baby boom wiped out a generation of women in science.

KEYWORDS: SCIENCE, INNOVATION, CHILDREN, GENDER EQUALITY, AND BABY BOOM.

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Women continue to be severely underrepresented in science,[1] and children are a possible cause. The American Time Use Survey (2018) documents that mothers carry a disproportionate share of the burden of parenting. For instance, married mothers working full-time spent an average of 72 minutes per day caring for their children compared with 49 minutes for married fathers.[2] Analyses of earnings have found that children contribute to the gender gap in earnings (e.g., Bertrand, Goldin, and Katz 2010, Klevens, Landais, and Soogard 2019).[3] Yet, systematic evidence on gender differences in *output* (or productivity) continues to be rare, especially when it comes to the effects of children.

This paper investigates whether children influence the *timing* of productivity, and whether such differences can help to explain the under-representation of women in science. To answer this question, we exploit a historical episode of exceptional fertility (the baby boom 1946-64) and unique data on children, productivity, and promotions for 82,094 American scientists in 1956, the height of the baby boom. Knowing each scientist's year of marriage allows us to pinpoint when they decided to have a family. Matching scientists with their patents and publications enables us to study changes in productivity over the life cycle.

To investigate the causal effects of children on productivity, we estimate event studies of changes in patenting after marriage. Using detailed data on each scientist's career history, we examine differences in the rate (and speed) of promotion to tenure. Examining the population of scientists in 1956, we can test whether and how elevated levels of fertility influenced who entered - and who survived - in American science.

Using a scientist's inventions as a measure of productivity, we show that mothers are substantially less productive in their 20s and 30s, both compared with men and with other women. After age 35, however, their output recovers, while that of other scientists declines.

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[1] Eight in ten women and minority students who enroll in science, technology, engineering and mathematics (STEM) drop out of college or switch out of STEM before they finish their undergraduate education (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] 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).

[3] Examining registry data for Denmark between 1980 and 2013, Klevens, Landais, and Soogard (2019) show that children reduced the earnings of women by 20 percent 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.

Mothers reach peak productivity at age 42, when they produce 6.5 additional patents (compared with their productivity at age 20). In contrast, fathers peak at age 35 (with 16.5 additional patents compared with themselves at age 20), and other women without children peak at age 30 (with 3.8 additional patents).

Event studies of changes in patenting after marriage show that mothers became less productive in the first decade but experienced a large and sustained productivity increase 15 years after marriage. Compared with their own productivity in the last year before marriage, mothers produce 6.8 additional patents per 100 scientists 20 years after their marriage. This late-in-life increase in productivity is unique to mothers. Output by other married women stays flat after age 35. In contrast, 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.

The unique timing of productivity is associated with large tenure penalties for mothers in science. Only 27 percent of female academics with children achieved tenure, compared with 48 percent of fathers and 46 percent of other women.[4] Counting from their first year as an assistant professors, mothers fall behind in terms of tenure rates after the first five years, and never catch up again to other demographic groups.

To help interpret these findings, we investigate selection into educational investments, tenure track jobs, marriage, parenting, research fields, and into "survival" as a scientist. Detailed data on university degrees allow us to examine investments in human capital in the form of PhDs. These data show that women who were scientists in 1956 were more likely to have earned a PhD compared with men, despite formal and informal barriers discouraging their entry in PhD programs.[5]

Examining selection into marriage, we find that female scientists were less than half as likely to marry compared with male scientists. 4 in 10 female scientists married, compared with 8 in 10 men. Female scientists also married later than men on average, even though women in

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[4] In a pattern suggestive of statistical discrimination, married women without children were also less likely to get tenure, at a rate of 29 percent.

[5] 84 percent of female scientists had earned a PhD, compared with 78 percent of male scientists. Parents of both genders were slightly less likely to hold a PhD compared with scientists of the same gender without kids.

the general population married two years earlier than men. Patent data reveal no evidence that mothers or married women were negatively selected. For instance, we find that married women were more productive than single women by age 27 (the median age of marriage for female scientists). Matching our data with faculty directories also shows women were much less likely to survive in science compared with men.

Employment records indicate that high levels of fertility during the baby boom created a lost generation of women in science. Among scientists who were active in 1956, there is a remarkable lack of women who would have been in their 20s during the baby boom. Using data on each scientist's first job and their university education, we document a dramatic decline in entry into science among women who were of child-bearing age at the beginning of the baby boom. These women and their contributions were lost to science.

I. Historical Background

After the end of World War II, more Americans than ever before married, had children, and stayed married. By 1960, only 27.4 percent of American women between the ages of 20 and 24 were single. Having increased during the war, divorce rates slowed to a low point of 8.9 per 1,000 women aged 15 and older, or just 368,000 divorces in 1958. Americans began to marry at a younger age. By 1950, the median age for an American woman at the time of her first marriage had fallen to 20.3 from 21.3 in 1930.

The combination of these factors led to a dramatic increase in births after the early 1940s lasting into the 1950s (Figure 1). 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.

1.1. More than 25 Births per 1,000 People, 1946-57

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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).

1.2. Women Bore and Raised Children in their 20s

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).

1.3 "Family Values" and Institutional Barriers

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

> 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 limited participation in both industry and academia. 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 percent of local school districts and about 50 percent of office workers (Goldin 1990, pp.160-61).

Academia was affected by similar restrictions, hindering the entry of women in the profession: "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. DATA: 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.[6] 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.[7] 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

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

[7] 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).

required for inclusion in the Directory." He also thanks "thousands of scientific men who have contributed names and information about those working in science," and "acknowledges the willing counsel of a special joint committee of the American Association for the Advancement of Science and the National Academy of Science National Research Council "which acted in an "advisory capacity" (Cattell 1956, Editor's Preface).

2.1.1. Identifying Female Scientists

To identify American scientists who are women, we use a Python library that assigns gender based on the share of women with the same name in US Social Security Administration records between 1880 and 2011.[8] Among 82,094 American scientists, 4,220 are women (5.1 percent), 66,560 are men (81.1 percent), and 11,314 have unknown gender (13.8 percent). 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 evaluate our assignment of gender, we have compared it with four alternative measures: 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). We also hand-checked a random sample of scientists and found few mistakes. Unsurprisingly, the gender detector algorithm performs poorly for Asian first names, which are rare both in the historical Social Security records and in the MoS. For example, gender detector assigns the chemist Dr. Miyoshi Ikawa (b.Venice, Calif. Feb 24, 1919, married 1950, 1 child) to be a woman. Yet images in Ikawa's funeral records (matched through name and the exact birth date) show that Ikawa was male. We create a separate algorithm to correct these names.

[8] Gender-detector 0.1.0 (available at https://pypi.org/project/gender-detector/: accessed June 25 2020). The code's author Jeremy B. Merrill describes the methodology 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 the level of statistical significance to 95 (which is also the default for the algorithm).

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 scientists and year. In addition, we use the scientists' ages to refine the matching of patents with scientists (by using patents by children as a proxy for false positives). Birth years are available for 99.2 percent of 82,094 American scientists in 1956, including 4,032 female scientists (95.6 percent) and 66,190 male scientists (99.5 percent).[9]

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.

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

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 percent of 4,032 women with gender and birth years) and 65,821 male scientists (99.4 percent of 66,198 men with gender and birth years).[10] The MoS (1956) reports undergraduate degrees for 3,755 of 4,032 female scientists (93.1 percent) and 61,005 of 66,198 male scientists (92.2 percent). PhD degrees and graduation years are recorded for 3,254 of 4,032 female scientists (80.7 percent) and 46,913 of 66,198 male scientists (70.9 percent).[11]

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*

Entries in the MoS include job titles and dates of employment; these data allow us to identify scientists who worked in academia and to examine differences in rates of promotion. To identify academics, we search teaching assistant, research assistant, research associate, research fellow, special fellow, instructor, visiting professor, clinical professor, adjunct professor, assistant professor, associate professor, professor, professor emeritus, dean, and department head. The indicator *academics* equals one for scientists who held one of these at least once.

Giuliana Tesoro, for example, 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." Therefore, the indicate *academic* equals zero for Tesoro. Another female scientist, Alice Dickinson Awtrey worked as an assistant professor and is recorded as an *academic*:

[10] Undergraduate degrees include Bachelor of Science, Bachelor of Arts, Bachelor of Chemistry, and Bachelor of Education (Appendix Figure A1).
[11] Other advanced degrees, including master's and MDs are recorded for 3,265 of 4,032 female scientists (81.0 percent) and 47,715 of 66,198 male scientists (72.1 percent).

> 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.

Three quarters, 52,946 of all 70,230 scientists in 1956, are academics. Separating the data by gender, 3,537 (87.7 percent) of 4,032 female scientists, and 49,409 (74.6 percent) of 66 198 male scientists are academics.

Together with data on employment years, job titles allow us to measure differences in the rate and the speed of promotions. Alice Awtrey became an assistant professor in 1953, five years after she graduated from Radcliffe in 1947 and two years after her PhD. For Awtrey, variable *undergraduate to prof* equals five and *PhD to prof* equals two.

The variable *tenure* equals 1 for scientists who have been promoted from the rank of an assistant professor to the rank of an associate or full professor. For Awtrey, *tenure* equals zero because she was still an assistant professor in 1956.

For scientists who were promoted to tenure, we calculate *time to tenure* as the number of years between the start year of an assistant professor position and the scientist's promotion to associate or full professor. Attie Lester Betts for example, started as an assistant professor in 1946, and was promoted to associate professor in 1948, so that *time to tenure* equals two:

> BETTS, PROF. ATTIE L(ESTER), Oklahoma Agricultural & Mechanical College, Stillwater, Okla. ELECTRICAL ENGINEERING. Fairy, Texas, July 30, 16; m. 40; c. 2. B.S, Agr. & Mech. Col. Texas, 38, M.S, 39, Ph.D (elec. Eng), 52. Grad. Asst. elec. eng, Agr. & Mech. Col, Texas, 38-39; engineer, Gulf States Utilities, 39-41; instr. ELEC. ENG, AGR. & MECH. Col, 41-42, 46, asst. prof, 46-48, assoc. prof, 48-52, PROF, 52- Sig. C, U.S.A, 42-46; U.S.A.R. Inst. Radio Eng. Supervisory control by UHF link; telemetering by UHF link; ultra-sonic treatment of dielectric materials; reflection from conducting materials; unconventional sources of electrical power.

2.1.6. Research Topics and Fields

A unique feature of the MoS (1921 and 1956) is that scientists list the topics of their research, along with their discipline. Attie Betts, for example, lists her discipline as "electrical engineering" and describes her research topics as "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, lists "organic chemistry" as her discipline and describes her research as "Synthesis of pharmaceuticals, textile chemicals, germicides and insecticides; synthesis and rearrangement of glycols in the hydrogenated naphthalene series." Disciplines are known for 99.97 percent; topics are known for 96.4 percent of all 82,094 American scientists in the MoS (1956).[12]

We use the data on research topics and discipline to assign each scientist to a unique research fields through *k*-means clustering (Moser and San 2020). Giuliana Tesoro, for example, is assigned to the research field "benzene" and Attie Betts to "materials science." Field assignments allow us to control for field-specific differences in patenting (e.g., Moser 2012). Moreover, we use these data to examine whether women (or parents) selected systematically into a certain set of research fields.

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.

The main specifications focus on the physical sciences (mainly chemistry, physics, engineering and mathematics), which roughly cover STEM (science, technology, engineering and mathematics). Most patents in the data are in the physical sciences (93.9 percent), and the match quality between scientists and patents is highest in these fields.[13] Data in the physical 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.

[12] Definitions of disciplines range from the extremely broad (such as "chemistry" or "physics") to very specific (such as "crystallographic chemistry" and "mathematical electrophysics").

[13] 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 percent, compared with 32.8 percent for the biological sciences and 67.9 percent for the social sciences. An important reason for these differences is that innovations in the biological and physical sciences were generally not patentable until the 1980s. See Moser and San (2020) for a detailed procedure of the matching procedure and the Data Appendix of this paper for summary statistics.

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.[14] 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 clean the matching and remove duplicates.

Our data include 754,581 journal publications by 46,102 scientists. 65.7 percent of 70,230 US scientists in the MoS (1956) have at least one publication. The average scientist has 10.8 publications (with a median of 2.0 and a standard deviation of 23.7). With 864 publications, Carl Djerassi, the inventor of the oral contraceptives, has the largest number of publications. Among female scientists, the embryologist and historian of science Jane Marion Oppenheimer has the largest number of publications, with 240.

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 and 3) have a similar first and last name, defining similarities as a Jaro-Winkler distance of 0.2.[15] 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

[14] 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."

[15] 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.

who are mothers (37.8 percent).[16] 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

To investigate how parenting influences the productivity of mothers compared with other scientists, we first examine differences in output – measured alternatively by patents and publications - across the four different demographic groups: mothers, fathers, and women and men without children.

3.1. Productivity Differences 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). Publications data indicate that mothers were slightly more productive than other women (with 87 and 83 publications, respectively, and significantly less productive than fathers (with 120 publications).

At least a portion of the 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:

$$y_{it} = \beta_1 Parent_i + \beta_2 Female_i + \beta_3 Female * Parent_i + \delta_t + \pi_b + \mu_f + \epsilon_{it} \quad (1)$$

where the dependent variable y_{it} counts US patents (or publications) per scientist i (multiplied by 100) in year *t*. The variable $Parent_i$ indicates scientists who were parents in 1956, $Female_i$

[16] 451 of 892 mothers had not yet married in 1940; 352 of them were below 27, the median age at marriage for female scientists.

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 invention across cohorts (e.g., as a result of changes in access to education to research opportunities during World War II). μ_f are field fixed effects to control for variation in the propensity to patent or publish across fields *f*. For example, scientists may patent less (but publish more) in theoretical fields, like mathematical analysis compared with applied fields, like chemical engineering. Field fixed effects control for these differences.

3.2. OLS Estimates for Patents

OLS estimates of differences in patenting confirm that mothers patent slightly more than other women but much less than fathers and other men. On average, female scientists produced 67 percent 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 percent) compared with a pre-baby boom mean of 8.811 patents per 100 scientist and year. Mothers patented 77 percent *less* than fathers (-5.870-0.912 in Table 2, column 1 divided by the mean), but 9 percent 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) and extending the analysis to the biological and social sciences (columns 4-5).

Mothers may have been more productive than other women 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 percent more than other men (283 patented inventions), and they published 1,191 papers, 9 percent 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).[17]

[17] Male MBAs with children have earnings that are 18 log points compared with childless men. While women's earnings decline sharply around three to four years after the birth of their first child (Bertrand et al. 2010, p. 248-9), MBA men with children see their earnings increase five years or more after the birth of their first child, and their labor supply is virtually unaffected. Goldin (1990, p. 102) shows that married men in manufacturing have earned 17 percent 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 for the

Intensity estimates for the *number* of children (Appendix Table A2) 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 1.772 additional patents per 100 scientist and year (Table 2, column 1, significant at 1 percent), equivalent to a 20.1 percent increase compared with the mean.

3.3. OLS Estimates for Publications

OLS estimates for differences in publications confirm the 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 73 percent fewer papers compared with men (based on an estimate of –12.166 for *female* Table 3, column 1, significant at 1 percent, relative to a pre-baby boom mean of 16.6 publications per 100 scientist and year). Confirming results based on patents, mothers published 83 percent less than fathers (with an estimate of -12.166 for *female* and -1.536 for *female*parent* in Table 3, column 1). As for patents, results are robust to controlling for age fixed effects (column 2) and including older scientists (column 3).

The most significant differences between our results from patents and publications arises for the comparison between mothers and other women in STEM. Mothers in STEM publish roughly the same as other women, while they patent slightly (8 percent) more than other women. Compared with other women, mothers in STEM produce eight percent additional patents, but they publish just the same as other women in STEM. These differences could be due either to differences in selection or in productivity: If mothers who patent are more likely to work in industry than academia, the difference in results may indicate that mothers in industry are more selected than mothers in academia. For example, mothers may be less able to accommodate long hours of laboratory work than other scientists, so that only the most productive among them survive. Another potential explanation for the difference is that motherhood reduces the publishing productivity of mothers in academia more than in science, if, for example, mothers are less likely to secure tenure. We will examine both of these potential channels below.

Another key advantage of incorporating publications along with patents as an output measure is that (with controls for variation across fields) publications are a good measure of

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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.

output across disciplines. Across all disciplines, female scientists published 62 percent fewer papers than men (with an estimate of -14.1 for *female* Table 3, column 4) compared with a pre-baby boom mean of 22.8 publications per 100 scientist and year. Mothers also published 67 percent less than fathers (with an estimate of -14.1 for *female* and -1.2 for *female*parent* in Table 3, column 1). Compared with other women, mothers publish slightly more across all disciplines (with an estimate of -1.2 for *female*parent* and 1.7 for *parent* Table 3, column 1).

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.

IV. DIFFERENTIAL CHANGES IN PRODUCTIVITY ACROSS THE LIFE CYCLE

How do children affect the timing of productivity? To investigate this question, we use biographical data on each scientist's date of birth to examine changes in productivity, again measured by patents and publications, across the life cycle of each scientist.

4.1. Patents across the Life Cycle of Scientists

Patents reveal a dramatic difference in the life cycle productivity of mothers compared with other scientists. Scientists who are mothers become more productive in their late 30s and early 40s, long after other scientists have started to decline. Mothers patent at a peak of 7.0 patents per 100 scientists and year of age at age 42, a 3-fold increase compared with their own productivity at age 27, the median age of marriage for female scientists (Figure A2, Panel A). 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 comparison, fathers peak at 37 (with 18.4 patents per 100 scientists and year, Figure A2, Panel A), and experience a continuous decline in productivity after 40. Notably, there are no significant differences in life cycle patterns of productivity between women and men without children (Figure A2, Panel B).

To investigate life-cycle productivity more systematically, we estimate OLS regressions

$$y_{ia}^{d} = \beta_{a}^{d} Age_{i} + \delta_{t} + \pi_{y} + \mu_{f} + \epsilon_{it} \quad (2)$$

where y_{ia}^{d} is the number of US patents (or publications) per 100 scientists i of demographic *d* in age *a*. Productivity is measured by patents (publications_ 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.

4.2. Age-Specific Estimates for Patents

For mothers, age-specific estimates of invention productivity increased after age 35 (Figure 2). Mothers increase their invention activity increases until age 27, the median age of marriage, when mothers produce 4.0 additional patents compared with themselves at 20 (Figure 2, 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 2). 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 2).

4.3. Age-Specific Estimates for Publications

Age-specific estimates for publications confirm the unique productivity patterns for mothers (Figure 3). Mothers' publications increase up to age 27, the median age at marriage for female scientists), reaching 31.2 additional publications (p=0.018) per year relative to their own output at age 20. However, mirroring the pattern for patents, mothers' publications trends fall behind those of other scientists after the median age of marriage and begin to recover from 25.1 additional publications at age 35 (p=0.000) to a late peak of 34.1 additional patents at age 42 (p=0.000). Confirming results for patents, this sharp increase in mothers' output occurs after the output of other scientists has flattened and started to decline.

V. EVENT STUDIES OF CHANGES IN PRODUCTIVITY

Changes in productivity across the life cycle suggest that mothers are less productive in their 20s to early 30s - at a period when many of them are pregnant or taking care of young children. We now investigate whether the temporary reduction in productivity during those years may be due to children. An ideal experiment to measure the causal effects of children on output would randomly assign children to scientists. Since this is impossible to do, we estimate event studies for marriage as a proxy for the birth of the first child. During the baby boom, most parents typically 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 around the year of 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. In addition, the event study approach allows us to trace out the long-run trajectory of productivity relative to the year of marriage. Event studies 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.[18]

5.1. Event Studies of Changes in Patenting after Marriage

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 4). In 7 of the first 15 years after marriage, estimates of β_s^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.

Confirming results for age-varying effects, this boost in output is unique to mothers and not shared by other demographic groups. In fact, event study estimates of β_s^f show that fathers (*parents* who are not *female*) become significantly more productive in the first 10 years of marriage (Figure 4). Compared with their own output in the year immediately preceding their marriage, fathers' productivity increases to 4.0 additional patents 5 years after marriage (p=0.000) and a peak of 5.6 additional patents 9 years after marriage (p=0.000). For fathers, productivity gains begin to decline after the first decade of marriage with 3.5 additional patents after 15 years (p=0.000) and 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_s^{om}) follow a similar pattern, increasing to a peak 9 years after marriage (5.3 additional patents, p=0.006), and a steady decline afterwards.

Estimates for other women (β_s^{ow}) remain close to estimates for mothers for the first 15 years, albeit with higher productivity in the early years of marriage. Yet, unlike the results for mothers, productivity continues to decline for other women after the first 15 years.

[18] 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 *y*.

VI. EFFECTS ON TENURE

In this section we examine whether a differential impact of parenting can help explain the "leaky pipeline" of promotions in academic science. Examining data for academic economists Dowell et al. (1999) have shown that women are less likely to be promoted than men, even though promotion opportunities for women (primarily from associate to full professors) have improved over time. Data on academic promotions show that women, and especially mothers, take a lot longer to get tenure starting from their undergraduate degree (Appendix Figure A6).

We use our data on American scientists to document gender inequality in promotions and explore whether parenting contributes to such inequality. Specifically, we examine differences in the transition from assistant professor to tenure. In addition to documenting differences in the rate of promotions, we examine differences in the *speed* of promotions.

6.1. Mothers – and Other Married Women - Were Less Likely to Get Tenure

Mothers were also much less likely to get tenure (Figure 5). Examining changes in the probability of tenure over time, we observe that mothers fell behind other scientists five years after their they became assistant professors. After five years the probability of a mother achieving tenure flattens, while the same probability for other scientists continues to increase.

As a result of this pattern, just 27 percent of mothers achieve tenure. Compared with fathers, mothers are 21 percent less likely to achieve tenure. (48 percent of fathers achieve tenure, Table 3). Compared with other women without children, mothers are 19 percent less likely to get tenure. (46 percent of other women become tenured professors, Table 3).

While mothers are heavily penalized for parenting, fathers are slightly more likely to get tenure than other men and also advance more quickly. 48 percent of fathers earned tenure, compared with 47 percent of other men without children. 44 in 100 fathers who were assistant professors attain tenure within 5 years of becoming an assistant professor, compared with 42 other men.[19]

[19] It is interesting to note that married women without kids also appear to have been penalized: Just 29 percent of married women achieved tenure. This marriage penalty may have been due in part to the expectation that married women would have kids. Married women were also penalized because they may have to move to accommodate their husband's career. In 1943, for example, a human resources officer of the US military's code-breaking operations at Arlington Hall wrote that married women were problematic "through no fault of their own but because they tended to move to follow their husbands" (Mundy 2018, p.52).

6.2. Event Study of Promotion to Tenure after Marriage

Extending the event study analyses to tenure, we estimate

$$y_{is}^{d} = \beta_s^d EventTime_i + \delta_t + \alpha_a + \mu_f + \epsilon_{it} \quad (4)$$

where the event time *y* is indexed 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 for the probability of promotion to tenure in event year *s* 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_s^m for mothers (Figure 6) indicate that the productivity penalty of motherhood created major long-run effects for the tenure rates of mothers. 15 years after marriage, mothers were 10.3 percent less likely to be promoted to tenure (p=0.025), compared with themselves in the last year before marriage. Moreover, the probability that a mother would achieve tenure continued to decline after the first 15 years of marriage - *even as their productivity increased*, as shown in Figure 4. After 20 years of marriage, mothers were 10.3 percent less likely to be promoted to tenure (p=0.040) and remain so throughout their careers, even though were more productive than their younger selves.

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

VII. 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.

7.1. 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.[20]

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).[21]

Yet, women who were active scientists in 1956 were *more likely* than men to have PhDs. 84 percent of female academic scientists in 1956 had a PhD compared with just 78 percent 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

[20] 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.

[21] 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).

to have a PhD: 83 percent of mothers had a PhD, compared with 84 percent of other women; 77 percent of fathers had a PhD, compared with 80 percent of other men.

7.2. Mothers Were Less Likely to Become Assistant Professors Than Fathers or Other Women

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 percent became assistant professors (Table 4), and most of them remained instructors for their entire careers. By comparison, 44.6 percent of other women without children, and 45.4 percent of fathers found a position as an assistant professor.

Importantly, this difference 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 choose academic science (Appendix Figure A9). 84.5 percent of mothers became academic scientists compared with 73.9 percent of fathers and 88.6 percent of other women (Table 4).[22]

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.

7.3. Selection into Marriage

Patent data show that female scientists who chose to marry were slightly *more* productive by the median age at marriage compared with other female scientists. 0.64 percent of married women had at least one patent by age 27 compared with just 0.57 percent of other women.[23]

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[22] Over time, the share of mothers pursuing academic jobs stays roughly constant, while other women become more likely to work exclusively in industry. 83 in 100 female scientists without children born between 1915 and 1925 work in academia at least once, compared with 90 in 100 born between 1895 and 1905. This trend for other women matches a similar shift away from academia for fathers and other men. Parents are slightly less likely to pursue an academic job across cohorts. 85 in 100 mothers work in academia at least once (compared with 89 other women) and 75 in 100 fathers are academics (compared with 77 other men).

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

Female scientists, however, were less than half as likely to marry compared with men. Just 38.8 percent of female scientists married, compared with 84.2 percent 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 percent of female scientists were married, compared with 79.1 percent of male scientists. Among the cohort of baby boom parents (scientists who were in their 20s in 1945), 51.0 percent of female scientists married, compared with 87.7 percent of men (Figure 7, Panel B).

Women also 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 A10). 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 A11). 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).

7.4. 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 percent, Table 1), but slightly less likely than married women without kids (9.7 percent). 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 percent for mothers compared with 0.65 percent of other women).

Yet, across all years, female scientists were less than one third as likely to have children compared with men. 22.1 percent of women who were scientists in 1956 had children, compared with 74.0 percent 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 (Figure 7, Panel B). For women, the share of parents among all scientists increased from 17.0 percent of women aged 40+ years in 1945 to 29.0 percent for women in their 20s. For men, the share of parents increased only slightly, from 71.5 percent to 74.8 percent.[24]

Female scientists also had many fewer children, with 0.41 children per female scientist, compared with 1.69 per male scientist (Figure 7, Panel C). Conditional on having any children, men had 2.3 compared with 1.9 for women (Figure 7, Panel D), again indicating that the most salient decision about parenting is at the extensive margin, between having any children or none.

In the baby boom cohorts, female scientists had more children, but still many fewer compared with male scientists. Women who were in their 20s in 1945 had an average of 0.55 children, compared with just 0.31 children for women who were in their 40s (Figure 7, Panel C). Male scientists always had between 1.6 to 1.7 children with minimal changes over time.

7.5. Selection into Research Fields

Patent data show that male scientists produce seven times as many patents as female scientists. One possible reason for this striking difference is that women select into research fields that are less competitive (Niederle and Vesterlund 2007)[25] or more "family friendly" (Goldin 2014, Goldin and Katz 2016). Kevles (1995, 1st ed. 1971, p 371) writes in *The Physicists. The History of a Scientific Community in America*:

> In any case 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.

Applying *k*-means to detailed data on scientists' disciplines and research topics, we investigate whether women were in fact less likely to pursue physics and other mathematical fields.

Our data show that women who worked in the physical sciences were six times as likely to be in physics compared with men. 3.7 percent of female scientists worked in physics,

[24] 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.

[25] 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.

compared with 0.6 percent of men (Appendix Figure A13). Other fields with high shares of women were chemistry (16.2 percent of female scientists, 11.5 percent of men), protein (6.9 percent female, 2.0 male), mathematical analysis (5.0 percent female scientists, 2.0 male), and radiation (3.7 percent of female scientists and 4.5 percent male).[26]

There do not appear to be significant differences in the choice of fields across mothers and other women (Appendix Figure A10), or between fathers and other men (Appendix Figure A11). For mothers and other women, the largest differences occur in x-ray crystallography, which had a larger share of mothers (2.4 percent compared with 0.8 for other women), and mathematical analysis, which had a smaller share of mothers (2.4 percent compared with 5.8 percent for other women). For fathers and other men, the largest differences occur in distillation, which had a larger share of fathers (3.2 percent compared with 2.7 for other men, Appendix Figure A11) and mathematical analysis, which had a smaller share of fathers (1.8 percent compared with 2.5 percent for other men).

Women were slightly less likely to work in fields with many patents, but these differences are relatively small (Appendix Figure A12). 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 -0.1697), and very close to zero, but positive for men (at 0.0006). There is also no evidence than mothers or fathers selected into fields that are less (or more) patenting intensive compared with other scientists (Appendix Figure A12).

7.6. 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

[26] The prominence of women in mathematical analysis and physics is striking, particularly considering the considerable barriers to entry faced by women. There is also some evidence that women, historically performed slightly worse in math tests. For instance, Blau et al (1998) report a gender gap in average math scores on the SAT of 46 points in 1977 and 35 points in 1996. Paglin and Rufolo (1990) show an 81-point difference in the quantitative section of the GRE and note that women are heavily underrepresented among high performers, the group with the largest share of majors in the physical sciences and in engineering. Tabulations from the National Longitudinal Survey of the High School Class of 1972 indicate that twelfth grade boys score higher on math and lower on reading and vocabulary (Brown and Corcoran 1997).

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.[27] We then use a combination of algorithmic and manual matching to identify scientists who were recorded in the MoS (1956).[28]

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 percent) survived to enter the MoS in 1956 (Table 5). In contrast, 793 (19.8 percent) of 4,003 male professors at the same universities survived to enter the MoS (1956). Just 20 (25.3 percent) of the 79 surviving scientists were mothers, compared with 584 (73.6 percent) of 793 surviving male scientists (Table 5).

VIII. AGGREGATE EFFECTS ON PARTICIPATION

In this section we investigate how changes in productivity and promotions at the individual level influenced the representation of women in science. Specifically, we compare changes in the number of women and men working as scientists in the United States each year.[29] These data reveal a large decline in entry by women after 1945. This decline was driven primarily by women who were in their 20s at the beginning of the baby boom.

8.1. Fewer Women Enter After 1945

Changes in the share of women among active scientists indicate that women's participation increased between 1930 and 1945 but declined afterwards (Appendix Figure A18, Panel A).[30] Between 1930 and 1945, the share of women scientists grew from 6.9 percent to 9.3 percent. 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 American scientists declines from

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[27] Faculty records for the California universities were obtained from the UC ClioMetric History Project (http://uccliometric.org/faculty/, accessed August 1 2020.

[28] Among 4,811 faculty members at Columbia, Stanford, UCLA, and UC Berkeley in 1943-45, 808 were women (16.8 percent) and 4,003 were men (83.2 percent).

[29] To determine the year when a scientist first entered US science, we combine information on scientists' employment and education. The year of a scientist's first US job or their first US university enrollment is known for 80,965 of 82,094 American scientists (98.6 percent, Moser and San 2020).

[30] Active scientists are defined by their age in a given year: Figure 3 plots the number of American scientists who were of working age (between 18 and 80 years) in year *t*.

a peak of 7.0 percent in 1945 to just 2.1 percent in 1950 and 1.6 percent in 1953. The next most affected cohort were women who were in their 30s in 1945, whose share declines from 1.7 percent in 1945 to 1.0 percent in 1950 and 0.3 percent in 1952.

8.2. A Missing Cohort of Baby Boom Mothers

Birth cohort comparisons indicate that women born between 1865 and 1915 made some progress towards closing the enormous underrepresentation of women in science (Figure 8). Between 1865 and 1898, the number of female scientists born per year increased 113-fold from a single female scientist in 1865 to 113 female scientists born in 1898. At the same time, the number of male scientists increased by 67.4-fold from 16 in 1865 to 1,062 in 1898. For women born after 1898, however, participation remained roughly constant around an average of 110 female scientists active in 1956 per birth year until 1915, while the number of male scientists more than doubles to 2,432 male scientists born in 1915.

For women born after 1915, participation declines both in absolute and relative terms (Figure 8). 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.

IX. CONCLUSIONS

Our analysis of detailed biographical data on more than 82,000 American scientists, including more than 4,000 women, at the height of the baby boom in 1956, has shown that childbirth led to a dramatic decline in the productivity of American scientists, measured by their patents. Parenting greatly reduced the rate of invention (measured by patents) by mothers in their 20s and 30s, both compared with men and compared with other women. This decline was particularly pronounced for women who were in their 20s at the beginning of the Baby Boom. By comparison, the productivity of fathers increased during their 20s and 30s (even controlling for time fixed effects).

Notably, the productivity of mothers picked up again after their mid-30s, when their children would have entered their teens. Mothers' productivity continued to increase until their late 40s, nearly a decade after the peak for men. Due to the cumulative nature of knowledge production, this delayed increase is unlikely to have represented a catch-up, as mothers patented ideas and research that they did while their children were young. Instead, we observe a selected sample of high-ability women who could return fully to science after they had taken care of young children.

Examining promotions, we find that female scientists were more likely to have a PhD, but less likely to advance to a tenure-track faculty position and especially tenure. Similar patterns hold today. 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 members (Barber 1995; Frehill et al. 2006; Kulis et al. 2002; Nelson and Rogers 2005; NSF 2003; Pell 1996). For instance, we find that women were 4.7 percent less likely to be hired into faculty positions compared with men. 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.

Our results indicate that parenting is a major driver of persistent gender inequality in STEM. Data on university degrees show that women with and without kids are more likely to earn their PhD than men. Mothers in academia, however, are 9.5 percent less likely to become assistant professors compared with fathers and 8.7 percent less compared with other women. Mothers also take 2.5 times longer (3.2 additional years) to enter the tenure track compared with fathers and 1.7 years longer than other women. Most strikingly, mothers who worked as academics are 21.0 percent less likely to get tenure than compared with fathers and 18.9 percent less likely compared with other women.

Do these results have any implications for today? Across industries, registry data for Denmark indicate the fraction of gender inequality caused by child penalties has intensified over the last three to four decades (Kleven, Landais, and Søgaard 2019). Survey data from the American Time Use Survey (2018) and many other sources indicate that, to this day, the burden of parenting falls disproportionately on women. Our results indicate that as long as such differences persist, there will be dramatic gender inequality in science.

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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
N	4,032	66,198	892	3,140	48,987	17,211
Share married	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	22.1%	74.0%	-			
Children	0.41	1.69	1.88	0.0	2.28	0.0
per scientist	(0.88)	(1.35)	(0.89)		(1.05)	
Patents	0.51	3.58	0.65	0.47	3.82	2.83
per scientist	(3.58)	(11.74)	(5.80)	(2.67)	(12.43)	(9.30)
Publications	8.35	11.65	8.73	8.25	11.91	10.90
per scientist	(15.48)	(25.51)	(17.02)	(15.02)	(26.30)	(23.07)

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 the STEM (chemistry, mathematics, and other STEM fields) by the total number of scientists in the STEM. *Publications per scientist* divides the total number of publications matched with scientists in the MoS (1956) by scientists by the total number of scientists in the MoS (1956).

TABLE 2 – EFFECTS OF CHILDREN ON PRODUCTIVITY MEASURED BY PATENTS

	Patents per 100 scientists per year				
	(1)	(2)	(3)	(4)	(5)
Female	-5.870***	-5.627***	-5.245***	-2.432***	-2.189***
	(0.173)	(0.174)	(0.156)	(0.067)	(0.061)
Parent	1.772***	1.898***	1.675***	1.186***	1.089***
	(0.135)	(0.138)	(0.125)	(0.068)	(0.063)
Female*Parent	-0.912**	-1.090***	-1.293***	-0.847***	-0.924***
	(0.389)	(0.391)	(0.366)	(0.125)	(0.116)
Year FE	Yes	Yes	Yes	Yes	Yes
Birth year FE	Yes	No	Yes	Yes	Yes
Age FE	No	Yes	No	No	No
Field FE	Yes	Yes	Yes	Yes	Yes
Disciplines	STEM	STEM	STEM	All	All
Scientists' age	18-65	18-65	18-80	18-65	18-80
N (scientists x years)	1,204,592	1,204,592	1,298,053	2,391,179	2,591,524
Pre-baby boom mean	8.811	8.811	8.752	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)-(5) include scientists across all disciplines, adding the biological sciences (biology and medicine) and social sciences (economics, psychology, and sociology).

TABLE 3 – EFFECTS OF CHILDREN ON PRODUCTIVITY MEASURED BY PUBLICATIONS

	Publications per 100 scientists per year				
	(1)	(2)	(3)	(4)	(5)
Female	-12.166***	-12.664***	-12.002***	-14.055***	-13.573***
	(0.426)	(0.422)	(0.387)	(0.297)	(0.273)
Parent	1.514***	0.693***	1.683***	1.682***	1.824***
	(0.215)	(0.208)	(0.203)	(0.173)	(0.162)
Female*Parent	-1.536*	-1.065	-1.048	-1.221*	-1.304**
	(0.855)	(0.849)	(0.837)	(0.644)	(0.608)
Year FE	Yes	Yes	Yes	Yes	Yes
Birth year FE	Yes	No	Yes	Yes	Yes
Age FE	No	Yes	No	No	No
Field FE	Yes	Yes	Yes	Yes	Yes
Disciplines	STEM	STEM	STEM	All	All
Scientists' age	18-65	18-65	18-80	18-65	18-80
N (scientists x years)	1,204,592	1,204,592	1,298,053	2,391,179	2,591,524
Pre-baby boom mean	16.588	16.588	16.592	22.776	22.787

*** 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 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 (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)-(5) include scientists across all disciplines, adding the biological sciences (biology and medicine) and social sciences (economics, psychology, and sociology).

TABLE 4 – SUMMARY STATISTICS ON PARTICIPATION AND CAREER PROFESSIONS 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	87.7%	74.6%	84.5%	88.6%	73.8%	77.1%
PhD / Academic	84.1%	77.5%	83.2%	84.4%	76.6%	79.8%
Tenure track / Academic	42.7%	45.5%	35.9%	44.6%	45.4%	45.9%
Tenured / Academic	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* divides the number of academic scientists (identified by their employment records) by the total number of scientists. *PhD / Academic* divides scientists with PhDs by the total number of academic scientists. *Tenure track / Academic* divides the number of assistant professors by the total number of academic scientists. *Tenured / Academic* 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

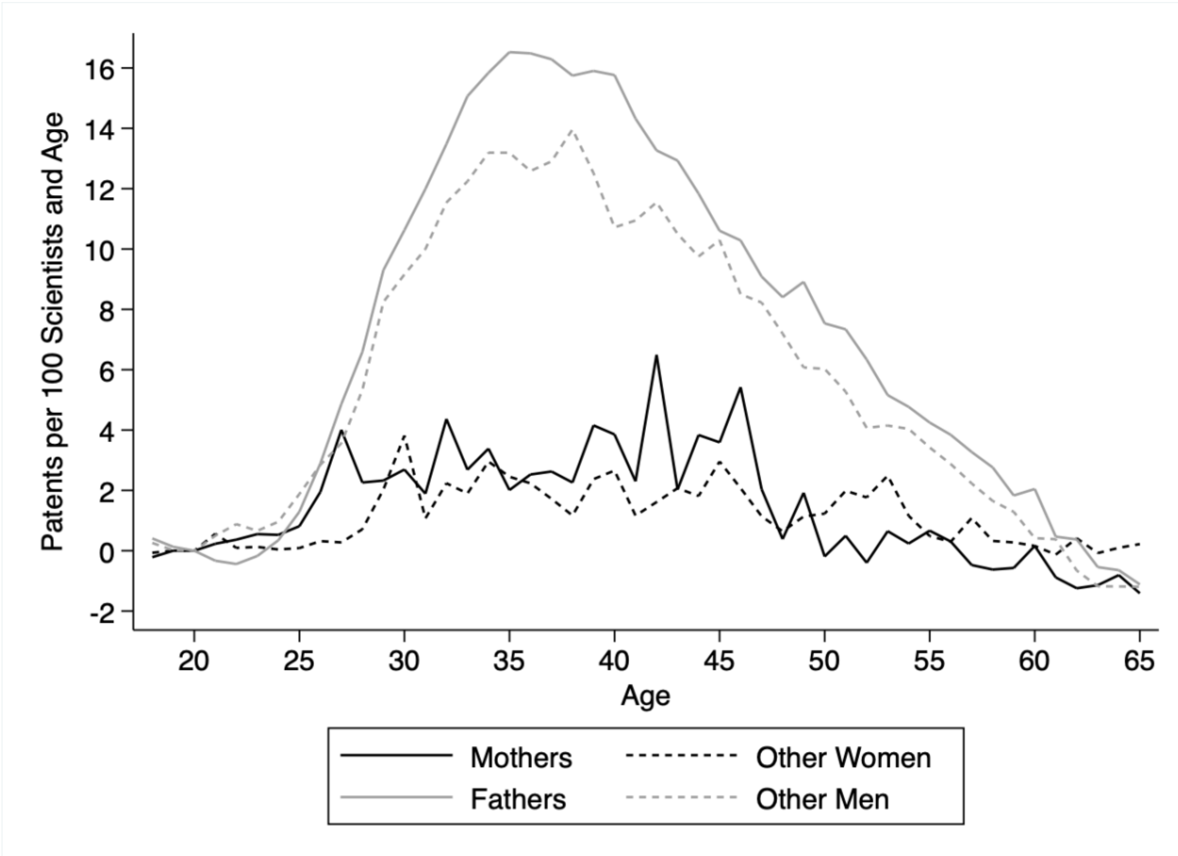
	All	All women	All men	Women		Men	
				with children	w/o children	with children	w/o children
N surviving	872	79	793	20	59	584	209
Columbia	385	46	339	11	35	255	84
Stanford	166	7	159	3	4	123	36
UC Berkeley	240	16	224	5	11	158	66
UCLA	95	12	83	1	11	57	26
Age in 1956	56.1	56.7	56.0	53.7	57.7	55.4	58.0
	(11.79)	(9.96)	(11.95)	(11.45)	(9.23)	(11.69)	(12.46)
Share married	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	69.3%	25.3%	73.6%	100%	0%	100%	0%
N children	1.63	0.49	1.74	1.95	0.0	2.36	0.0
	(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 – 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 2 – AGE-VARYING ESTIMATES OF PRODUCTIVITY MEASURED BY PATENTS

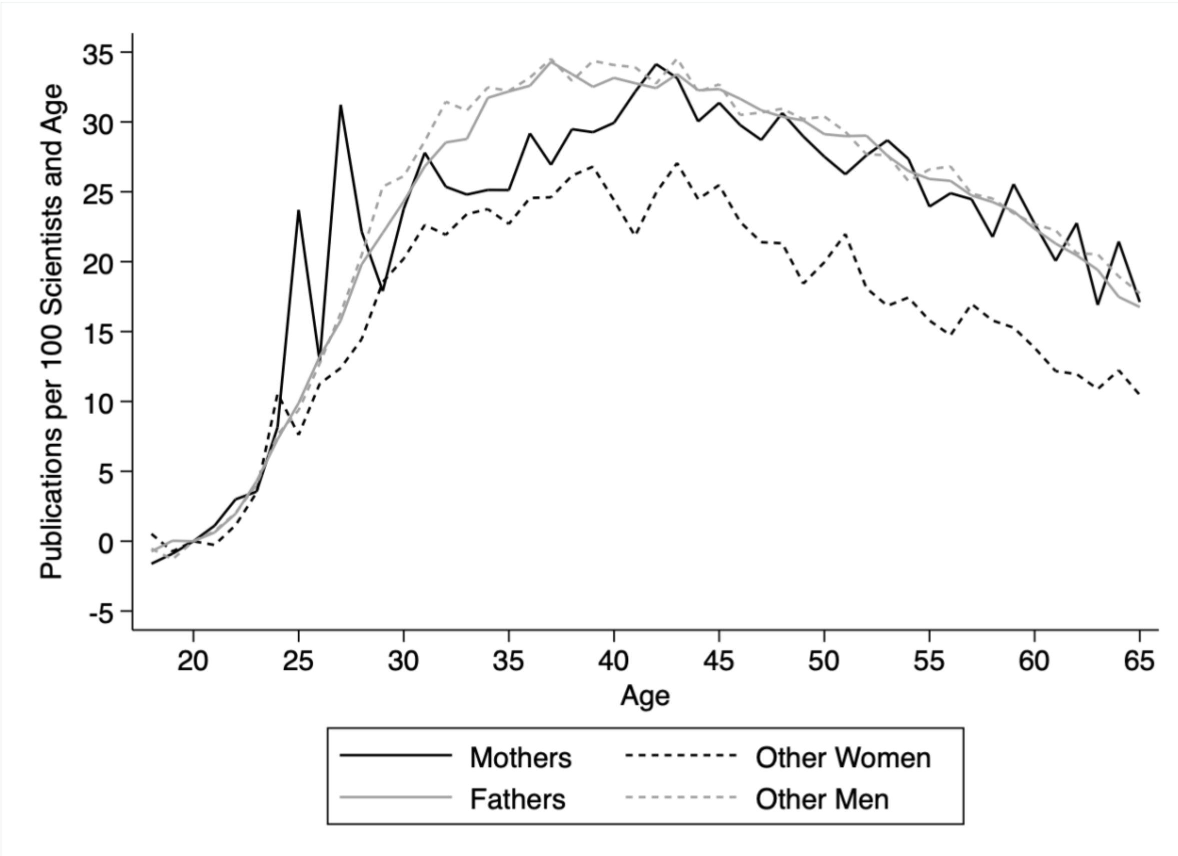


Notes: OLS estimates of β_a^d for demographic d (mothers, fathers, other women, and other men) in the regression:

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

where y_{ia}^d is the number of US patents per scientist i (multiplied by 100) of demographic d in age a. Productivity is measured by patents in year t per 100 scientists of age a in year t of the patent application. The coefficient β_a^d is a vector of age-varying estimates of inventions 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 military service). Field year fixed effects μ_f control for variation in the invention intensity and in the propensity to patent inventions (Moser 2012) across fields f. Regressions with patent data are estimated for the physical sciences, including a total of 35,368 scientists, 252 of which are mothers, 920 other women (without children), 25,829 fathers, and 8,367 other men.

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 regression:

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

where y_{ia}^d is the number of publications per scientist i (multiplied by 100) of demographic *d* who received tenure by 1956 in age a. 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 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 military service). Field year fixed effects μ_f control for variation in the publishing intensity across fields *f*. Regressions with publication data are estimated for all scientists in any discipline, including a total of 70,230 scientists, 892 of which are mothers, 3,140 other women (without children), 48,987 fathers, and 17,211 other men.

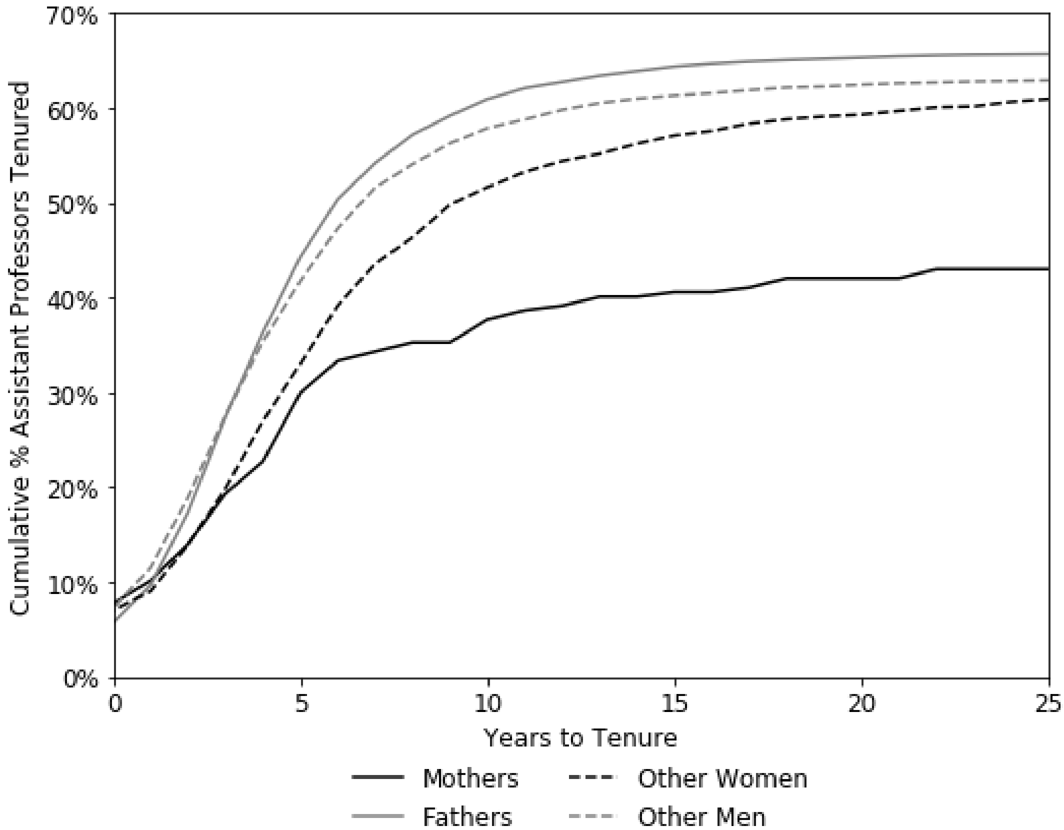
FIGURE 4 – EVENT STUDIES OF CHANGES IN PATENTING AFTER MARRIAGE

Notes: OLS estimates of β_s^d for demographic d (mothers, fathers, other married women, and other married men) in the regression:

$$y_{is}^d = \beta_s^d EventTime_i + \delta_t + \alpha_a + \mu_f + \epsilon_{it}$$

where y_{is}^d is the number of patents per scientist i (multiplied by 100) of demographic d in year relative to marriage s. Productivity is measured by patents in year y after marriage per 100 scientists in demographic group d in year t of the patent application. The coefficient β_s^d is a vector of time-varying estimates of inventions in event year s relative to 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 to capture variation in invention intensity over time (e.g., as a result of variation in research funding); α_a are age fixed effects to control for variation in patenting across the life cycle of scientists. Field year fixed effects μ_f control for variation in the invention intensity and in the propensity to patent inventions (Moser 2012) across fields f. Data include 29,954 married scientists in the physical sciences; 239 of them are mothers, 227 other married women without children, 24,777 fathers, and 4,711 other married men.

FIGURE 5 – 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 *Years to Tenure* counting from the start year of their first assistant professor job. Data include 18,793 academic scientists in the physical, biological, or social sciences who list an assistant professor job in their employment records; 207 of them are mothers, 1,042 other women (without children), 12,757 fathers, and 4,787 other men.

FIGURE 6 – EVENT STUDY OF CHANGES IN THE PROBABILITY OF TENURE AFTER MARRIAGE

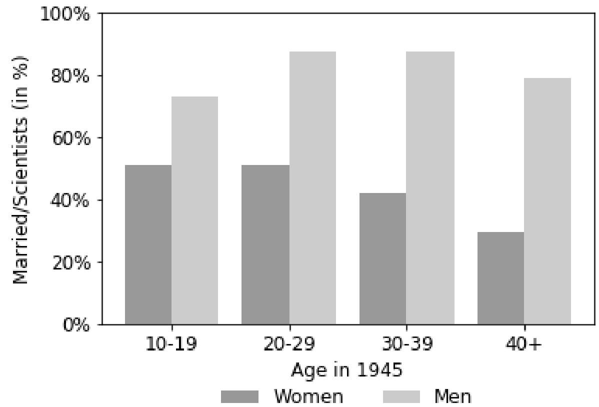
Notes: OLS estimates of β_s^d for demographic d (mothers, fathers, other married women, and other married men) in the regression:

$$y_{is}^d = \beta_s^d EventTime_i + \delta_t + \alpha_a + \mu_f + \epsilon_{it}$$

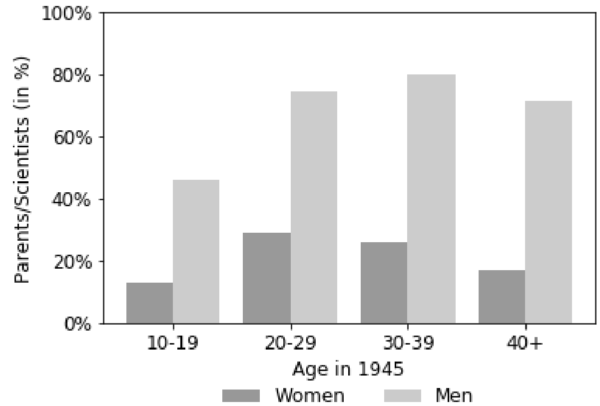
where y_{is}^d indicates whether scientist i of demographic d was promoted to tenure in event year s relative to marriage. The coefficient β_s^d is a vector of time-varying estimates for the probability of promotion to tenure in event year s after marriage for a scientist of demographic d relative to probability of promotion to tenure in the year before marriage. δ_t are publication year fixed effects to capture variation in invention 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, and μ_f are field fixed effects to control for variation in the publishing intensity across fields *f*. Data include 14,931 married academic scientists in the physical, biological, and social sciences who report having had an assistant professor job. Among them, 194 are mothers, 192 other married women, 12,175 fathers, and 2,370 other married men who were assistant professors.

FIGURE 7 – SELECTION INTO MARRIAGE AND PARENTING:

PANEL A: SHARE OF MARRIED SCIENTISTS



PANEL B: SHARE OF PARENTS

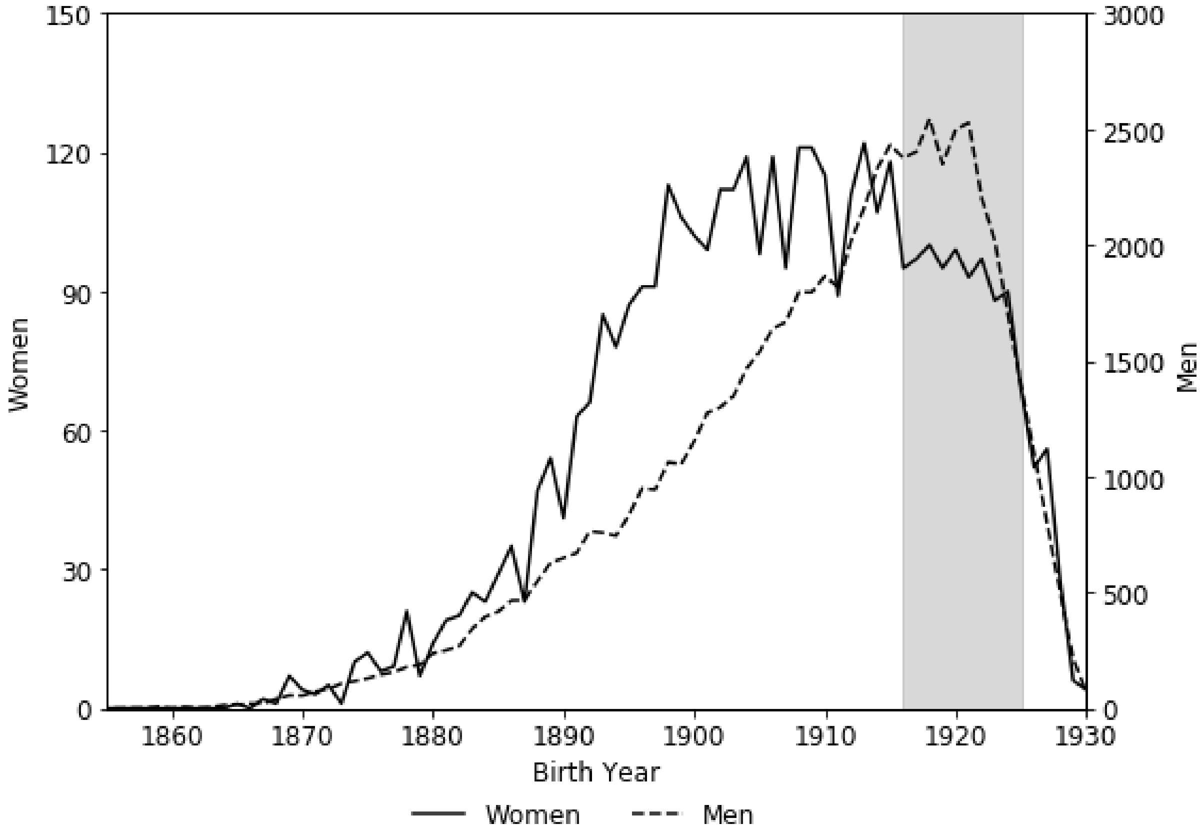


PANEL C: NUMBER OF CHILDREN PER SCIENTIST

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 8 – 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: Matching Scientists with Patents

To match scientists with patents, we start from a standard Levenshtein (1966) measure (allowing one letter to differ between the name of the scientist and the inventor) and use the scientist's age to filter out false positives. First, we exclude all patents whose application predates the scientist's birth or postdates their 80th birthday. This leaves 1,897,128 patents by 82,094 scientists between 1910 and 1970 (92.5 percent of the original matches). Next, we use patents that the inventor would have filed between the ages of 0 and 17 as a proxy for false positives and develop a matching procedure that reduces the error rate.

Under the assumption that false positive matches are distributed uniformly across the age profile of an inventor, we can use patent applications by children to estimate the rate of false positive (type I) errors

$$Error\ Rate = \frac{False\ Positives_{18-80}}{Total\ Matches_{18-80}} \quad \text{(A1)}$$

where $False\ Positives_{18-80}$ counts false positive matches between scientists and patents for scientists between the ages of 18 and 80 and $Total\ Matches_{18-80}$ is the total number of matches between scientists and patents for scientists of the same age.

$Total\ Matches_{18-80}$ are observable in the data, and we need to estimate $False\ Positives_{18-80}$. Let m_{ia} be the number of matched patent scientist pairs for scientist i at ages a and let e_{ia} be the number of false positive matches between scientists and patents. Then,

$$False\ Positives_{18-80} = \sum_{a\,=\,18}^{80} \sum_{i\,=\,1}^{N_a} e_{ia} \quad \text{(A2)}$$

where N_a is the total number of scientists of age a in the data. Because our sample is restricted to patents between 1910-1970, we only keep scientist-age observations (a, i) for which $1910 \leq b_i + \mathrm{a} \leq 1970$ where b_i is the birth-year of scientist i.

Next, we use patents that the inventor would have filed between the ages of 0 and 17 as a proxy for false positives. While there is no age restriction on patents, applications by children are exceptional. Under the assumption that false positive matches are distributed uniformly across different ages of an inventor, we can use patent applications by children to estimate the rate of false positive.

Specifically, for each age between 18-80, we assume that the average error matchings per scientist is equal to the average number of matchings per scientist that we observed for scientists between the ages of 0 and 17. If the average number of matchings per scientist at age a is lower than the average for ages 0 to 17, we assume that all matched patent-scientists pairs at that age are false positive matches. Defining

$$\bar{e}_a = \frac{1}{N_a}\sum_{i=1}^{N_a} e_{ia}, and\ \bar{m}_a = \frac{1}{N_a}\sum_{i=1}^{N_a} m_{ia} \quad \text{(A3)}$$

our assumptions imply

$$\bar{\mathrm{e}}_{\mathrm{a}} = \min\left(\frac{1}{18}\sum_{\tilde{\mathrm{a}}=0}^{17} \bar{\mathrm{m}}_{\tilde{\mathrm{a}}}, \bar{\mathrm{m}}_{\mathrm{a}}\right) \quad \text{(A4)}$$

Substituting into equation (B2), we obtain

$$False\ Positives_{18-80} = \sum_{a=18}^{80} \bar{e}_a N_a \quad \text{(A5)}$$

and the error rate is

$$Error\ Rate = \frac{\sum_{\mathrm{a}=18}^{80} \bar{\mathrm{e}}_{\mathrm{a}} \mathrm{N}_{\mathrm{a}}}{\sum_{\mathrm{a}=18}^{80} \bar{\mathrm{m}}_{\mathrm{a}} \mathrm{N}_{\mathrm{a}}} \quad \text{(A6)}$$

Using this measure, a naïve Levenshtein matching yields an error rate of 83.3 percent across all disciplines, suggesting that more than four in five "matches" are false positive (Appendix Table A1, Panel A). Notably, the error rate is much lower in the physical sciences (75.0 percent) than in the biological and social sciences (with 96.2 and 92.9 percent, respectively).

To reduce error, we first match scientists with patents using their middle name or middle initial, defining two conditions for a scientist-inventor pair to be a middle name match. First, the scientist and the inventor must have the same number of names (e.g., three names including one middle name or two names without any middle name). Second, if the scientist and the inventor both have a middle name, their middle name must have the same initial or the same middle name. For example, Aarons W. Melvin" and "Aarons Wolf Melvin" are middle name matches, while "Robert A. Lester," "Robert Lee Lester" or "Arthur Dwight Smith" and "Arthur Dean Smith" are not. With middle name matching, the rate of false positives declines from 75.0 to 14.2 percent in the physical sciences but stays high for the biological and social sciences at 72.3 and 81.6 percent, respectively (Appendix Table A1, Panel B).

In the final step of the matching, we exclude the top quintile of common names, like John

Smith. (To calculate the frequency of a scientist's name, we multiply the probability of their first name in social security records 1880-2013 by the probability of their last name in the US Census 2000.) Excluding common names further reduces the error rate from 22.1 to 6.3 percent. Controlling for middle names and dropping the top quintile of frequent names reduces this rate to 4.2 percent for the physical sciences. Error rates for the biological and social sciences remain high at 32.8 and 67.9 percent (Appendix Table A1, Panel C), which is consistent with inter-industry differences in the propensity to patent (Cohen, Nelson and Walsh 2000, Moser 2012).

TABLE A1 – MATCHING SCIENTISTS WITH PATENTS

	All	Physical Sciences	Biological Sciences	Social Sciences
Scientists in MoS (1956)	82,094	41,096	25,505	15,493
A. Patent applications made when scientists are 18-80 years old				
Scientists with at least 1 patent	43,929	27,527	10,777	5,625
Patents	1,496,170	887,658	384,058	224,454
Patents per scientist	18.23	21.60	15.06	14.49
Error rate	83.3%	75.0%	96.2%	92.9%
B. Scientists and patentees have matching middle names				
Scientists with at least 1 patent	27,030	20,743	4,506	1,781
Patents	250,707	216,475	23,113	11,119
Patents per scientist	3.05	5.27	0.91	0.72
Error rate	22.1%	14.2%	72.3%	81.6%
C. Matching middle name & excluding frequent names				
Scientists with at least 1 patent	18,035	15,146	2,311	578
Patents	164,892	154,883	8,064	1,945
Patents per scientist	2.01	3.77	0.32	0.13
Error rate	6.3%	4.2%	32.8%	67.9%

Notes: Panel A reports statistics on patents for which scientists would have applied between the age of 18 and 80, excluding applications between the ages 0 and 17 and above 80. Panel B reports scientists-patent pairs with a matching middle name. Panel C excludes the top five percent of common names.

APPENDIX B: 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 A2 – EFFECTS OF HAVING MORE CHILDREN ON THE PRODUCTIVITY OF MALE AND FEMALE SCIENTISTS

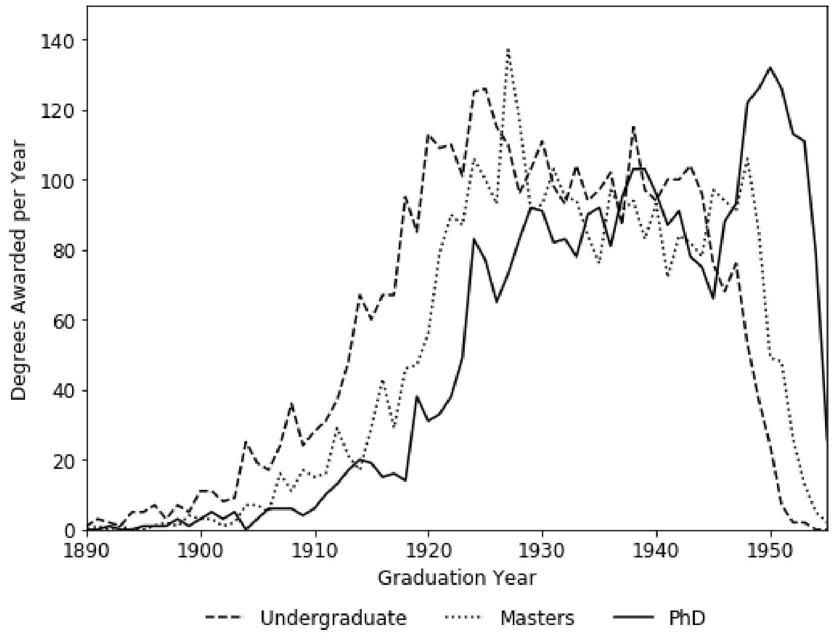
	Patents per 100 scientists per year				
	(1)	(2)	(3)	(4)	(5)
Female	-5.870***	-5.628***	-5.245***	-4.108***	-3.730***
	(0.173)	(0.174)	(0.156)	(0.068)	(0.061)
1 Child	1.669***	1.822***	1.558***	1.624***	1.494***
	(0.185)	(0.186)	(0.171)	(0.098)	(0.090)
2 Children	1.838***	1.950***	1.717***	1.687***	1.565***
	(0.160)	(0.165)	(0.149)	(0.082)	(0.076)
3+ Children	1.781***	1.886***	1.712***	1.496***	1.410***
	(0.168)	(0.166)	(0.157)	(0.085)	(0.079)
Female*1 Child	-2.284***	-2.589***	-2.664***	-1.724***	-1.758***
	(0.374)	(0.386)	(0.347)	(0.132)	(0.122)
Female*2 Children	0.535	0.490	0.127	-1.267***	-1.319***
	(0.763)	(0.761)	(0.730)	(0.232)	(0.218)
Female*3+ Children	-1.316***	-1.582***	-1.539***	-1.902***	-2.027***
	(0.331)	(0.349)	(0.306)	(0.107)	(0.010)
Year FE	Yes	Yes	Yes	Yes	Yes
Birth Year FE	Yes	No	Yes	Yes	Yes
Age FE	No	Yes	No	No	No
Field FE	Yes	Yes	Yes	No	No
Disciplines	STEM	STEM	STEM	All	All
Scientists' age	18-65	18-65	18-80	18-65	18-80
N (scientists x years)	1,204,592	1,204,592	1,298,053	2,391,179	2,591,524
Pre-baby boom mean	8.811	8.811	8.752	4.606	4.579

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

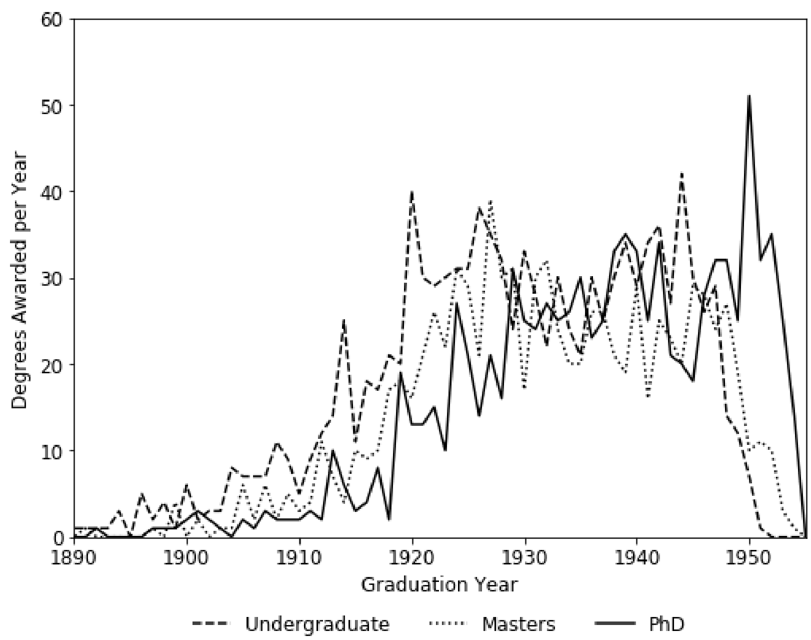
Notes: OLS estimates compare changes in the number of US patents by US scientists in the physical sciences per year throughout 1930–1970. Column (1) estimates $y_{it} = \beta_1 Parent_i + \beta_2 x\ Child_i + \beta_3 Female * x\ Child_i + \delta_t + \pi_b + \mu_f + \epsilon_{it}$, where the dependent 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. Columns (2)-(5) follow identical structures as Columns (2)-(5) from Table 5.

FIGURE A1 – ACADEMIC DEGREES AWARDED TO WOMEN ACTIVE IN AMERICAN SCIENCE IN 1956

PANEL A: ALL DISCIPLINES



PANEL B: PHYSICAL SCIENCES



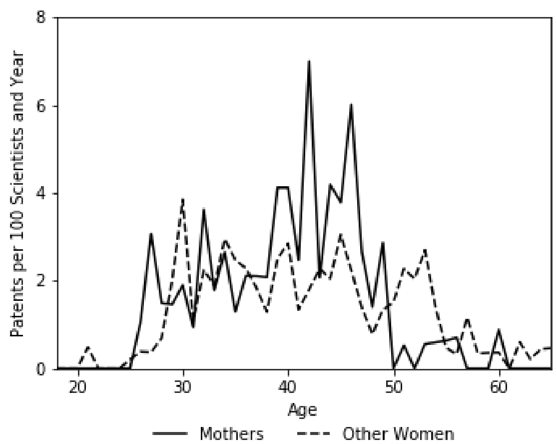
Notes: Degrees awarded per year to women who were active in American science in 1956. Panel A shows degrees for 4,032 female scientists in all disciplines (including the physical, biological, and social sciences, with a total of 3,755 undergraduate degrees, 3,265 master's, and 3,254 PhDs. Panel B plots degrees for 1,172 women in the physical sciences, with 1,120 undergraduate degrees, 900 master's, and 960 PhDs.

FIGURE A2 – PRODUCTIVITY CHANGES ACROSS THE LIFE CYCLE OF SCIENTISTS

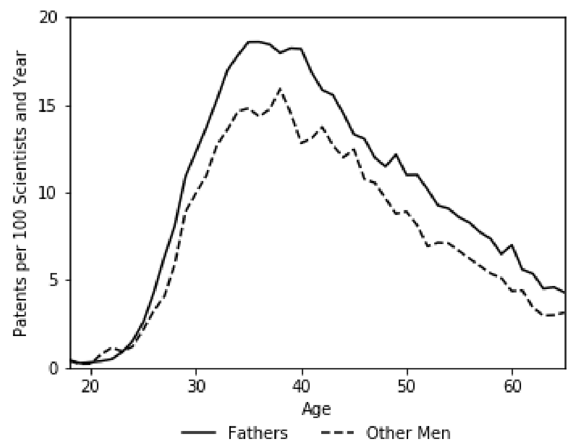
PANEL A: MOTHERS VS FATHERS

PANEL B: MEN VS WOMEN W/O CHILDREN

PANEL C: MOTHERS VS OTHER WOMEN



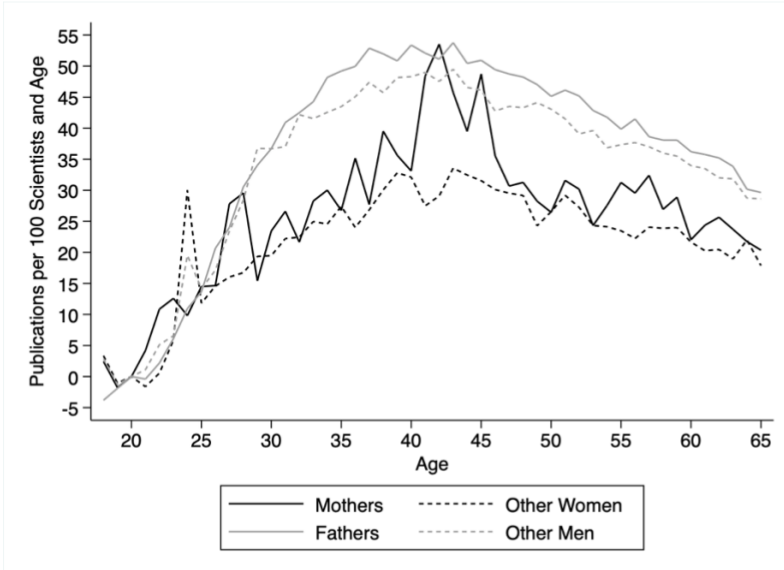
PANEL D: FATHERS VS OTHER MEN



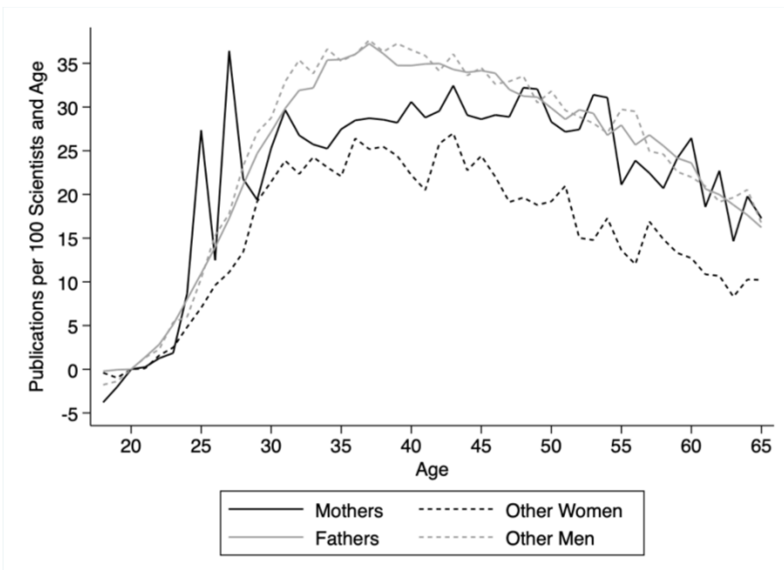
Notes: Panel A: 97,608 patents by 26,081 American scientists in the physical sciences, including 252 women and 25,829 men, who were active in US science in 1956 and had at least one child. *Panel B:* 23,713 patents by 9,287 American scientists in the physical sciences, including 920 women and 8,367 men, who were active in US science in 1956, are not parents, and whose gender and birth years are known. *Panel C:* 589 patents by 1,172 female American scientists in the physical sciences, 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 the physical sciences, 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 – AGE-VARYING ESTIMATES OF PRODUCTIVITY MEASURED BY PUBLICATIONS

PANEL A: ACADEMICS WITH TENURE



PANEL B: ACADEMICS WITHOUT TENURE



Notes: OLS estimates of β_a^d for demographic d (mothers, fathers, other women, and other men) in the regression:

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

Where variables y_{ia}^d, β_a^d, δ_t, π_y, and μ_f are identical to those in Figure 3. *Panel A:* Associate and full professors in any discipline, including a total of 25,019 scientists, 202 of which are mothers, 1,272 other women (without children), 17,280 fathers, and 6,265 other men. *Panel B:* Associate and full professors in any discipline, including a total of 45,211 scientists, 690 of which are mothers, 1,868 other women (without children), 31,707 fathers, and 10,946 other men.

FIGURE A4 – EVENT STUDIES OF CHANGES IN PUBLISHING AFTER MARRIAGE

Notes: OLS estimates of β_s^d for demographic *d* (mothers, fathers, other married women, and other married men) in the regression:

$$y_{is}^d = \beta_s^d EventTime_i + \delta_t + \alpha_a + \mu_f + \epsilon_{it}$$

where y_{is}^d is the number of publications per scientist i (multiplied by 100) of demographic *d* in year relative to marriage *s*. Productivity is measured by publications in event year *s* after marriage per 100 scientists in demographic group *d* in year *t* of the patent application. The coefficient β_s^d is a vector of time-varying estimates of publications in event year *s* relative to marriage by scientists of demographic *d* compared with scientists in the same demographic one year before they married. 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 57,336 married scientists; 832 of them are mothers, 734 other married women without children, 46,837 fathers, and 8,933 other married men.

FIGURE A5 – EVENT STUDIES OF CHANGES IN PUBLISHING AFTER MARRIAGE

PANEL A: ACADEMICS WITH TENURE

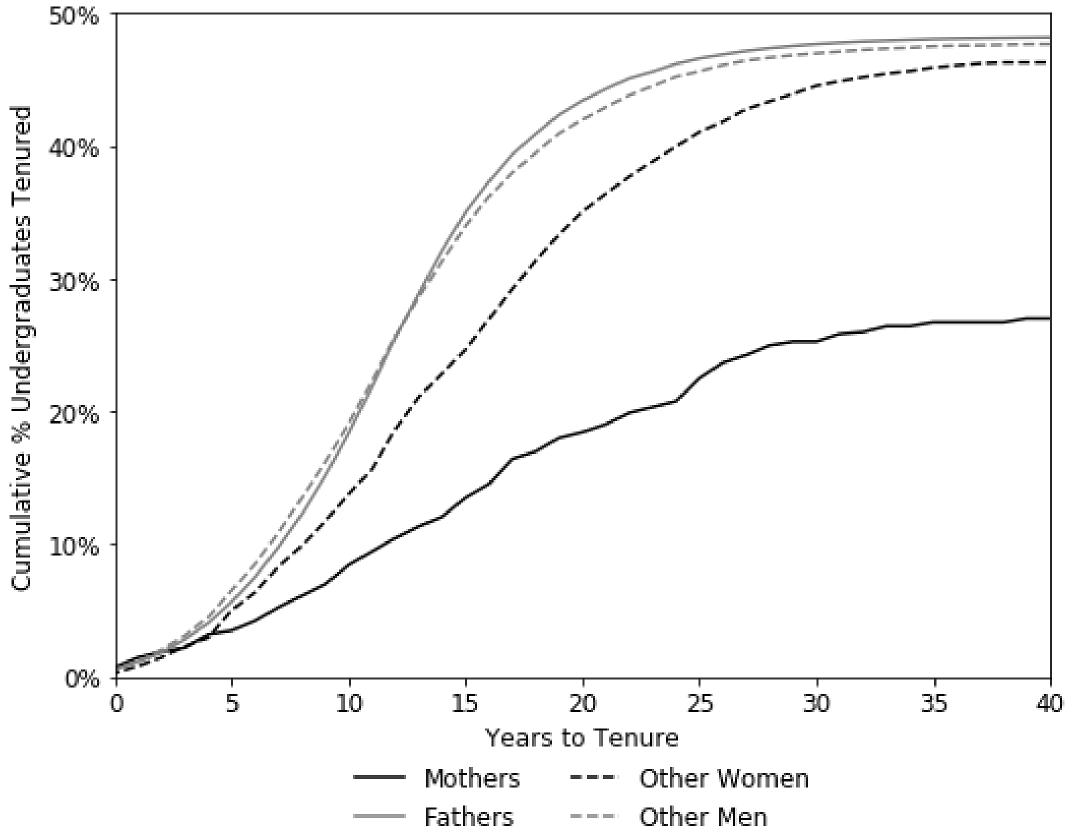
PANEL B: ACADEMICS WITHOUT TENURE

Notes: OLS estimates of β_s^d for demographic d (mothers, fathers, other married women, and other married men) in the regression:

$$y_{is}^d = \beta_s^d EventTime_i + \delta_t + \alpha_a + \mu_f + \epsilon_{it}$$

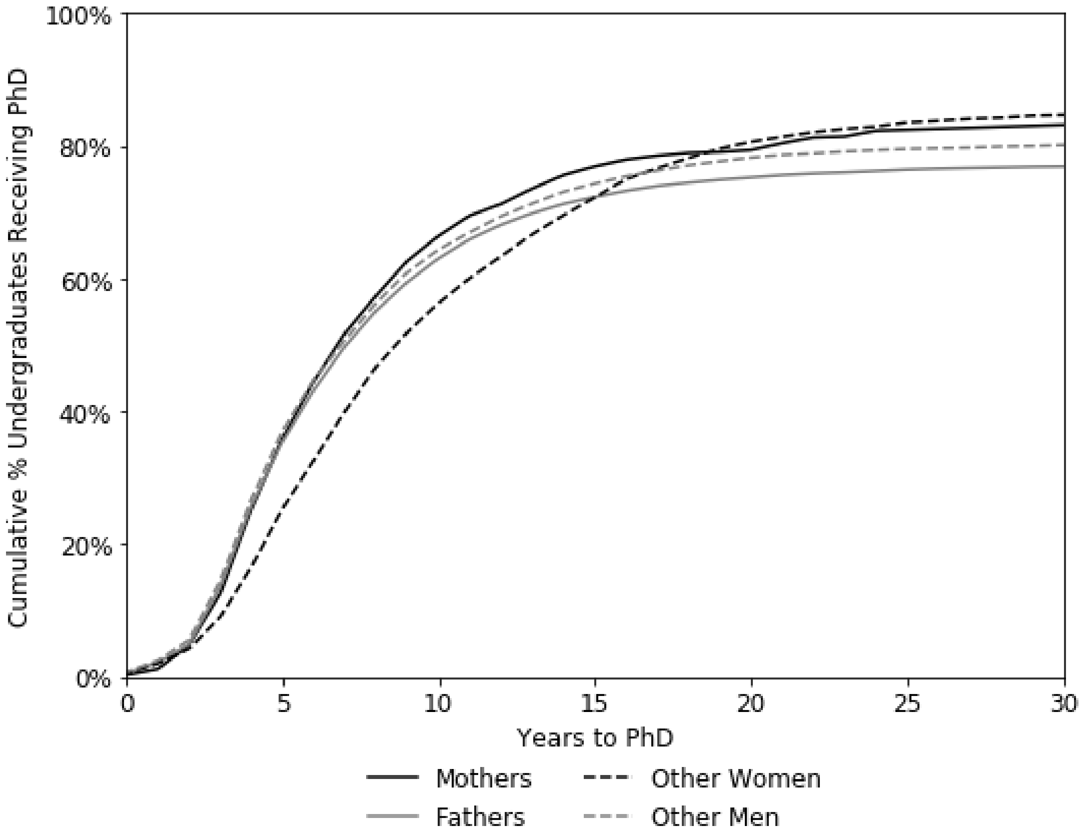
Where variables y_{is}^d, β_s^d, δ_t, α_a, and μ_f are identical to those in Appendix Figure. *Panel A:* Data include 19,414 married scientists who become associate or full professors; 190 of them are mothers, 186 other married women without children, 16,272 fathers, and 2,766 other married men. *Panel B: Panel A:* Data include 37,922 married scientists who were academics but did not attain tenure; 642 of them are mothers, 548 other married women without children, 30,565 fathers, and 6,167 other married men.

FIGURE A6 – SPEED OF PROMOTION TO TENURE, COUNTING FROM UNDERGRADUATE DEGREE



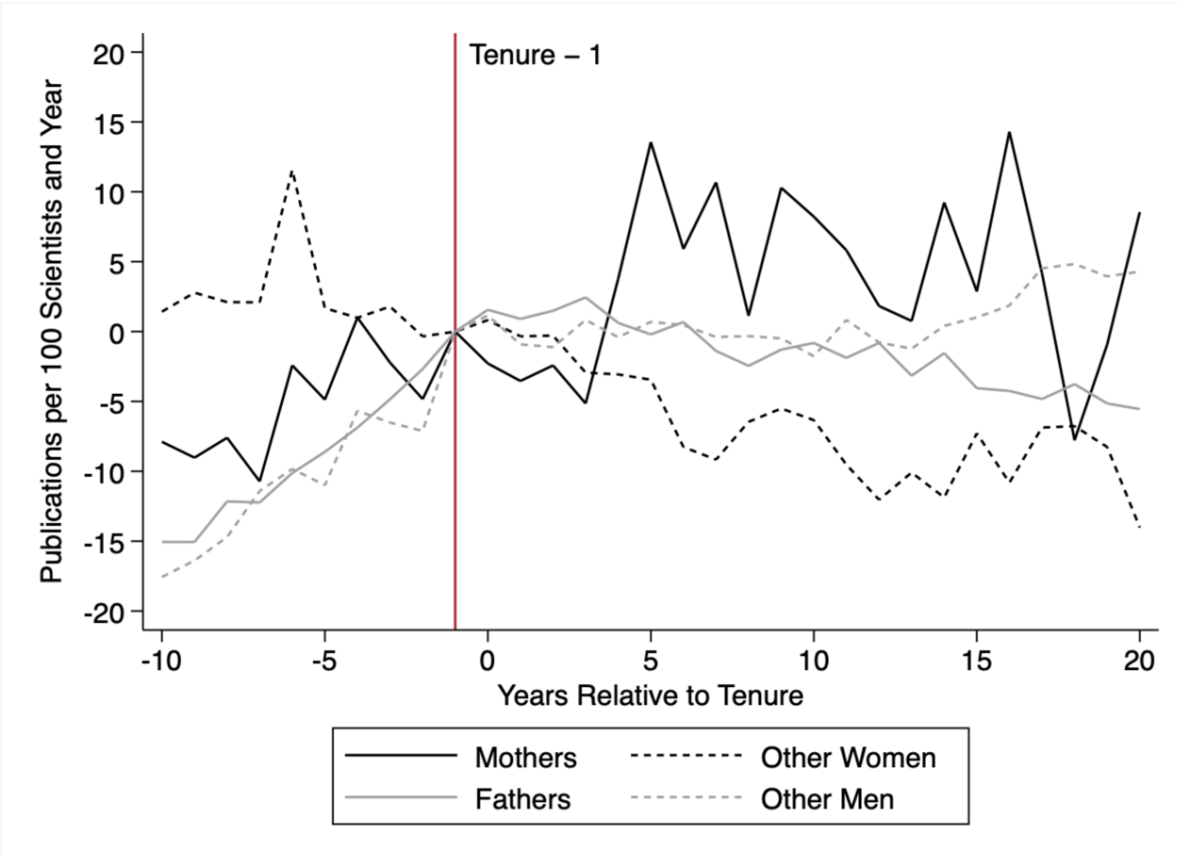
Notes: Years it takes to become a tenured professor (associate or full), counting from the year of receiving an undergraduate degree. Data include 689 mothers, 2,616 other women, 33,276 fathers, and 12,070 other men who received undergraduate degrees and were academics, of which 186 mothers, 1,216 other women, 16,062 fathers, and 5,770 other men later become tenured.

FIGURE A7 – SPEED TO PHD, COUNTING FROM UNDERGRADUATE



Notes: Years it takes to receive a PhD, counting from the year of receiving an undergraduate degree. Data include 689 mothers, 2,616 other women, 33,276 fathers, and 12,070 other men who received undergraduate degrees and were academics, of which 574 mothers, 2,225 other women, 25,788 fathers, and 9,757 other men later receive their PhDs.

FIGURE A8 – EVENT STUDIES OF CHANGES IN PUBLISHING AFTER TENURE

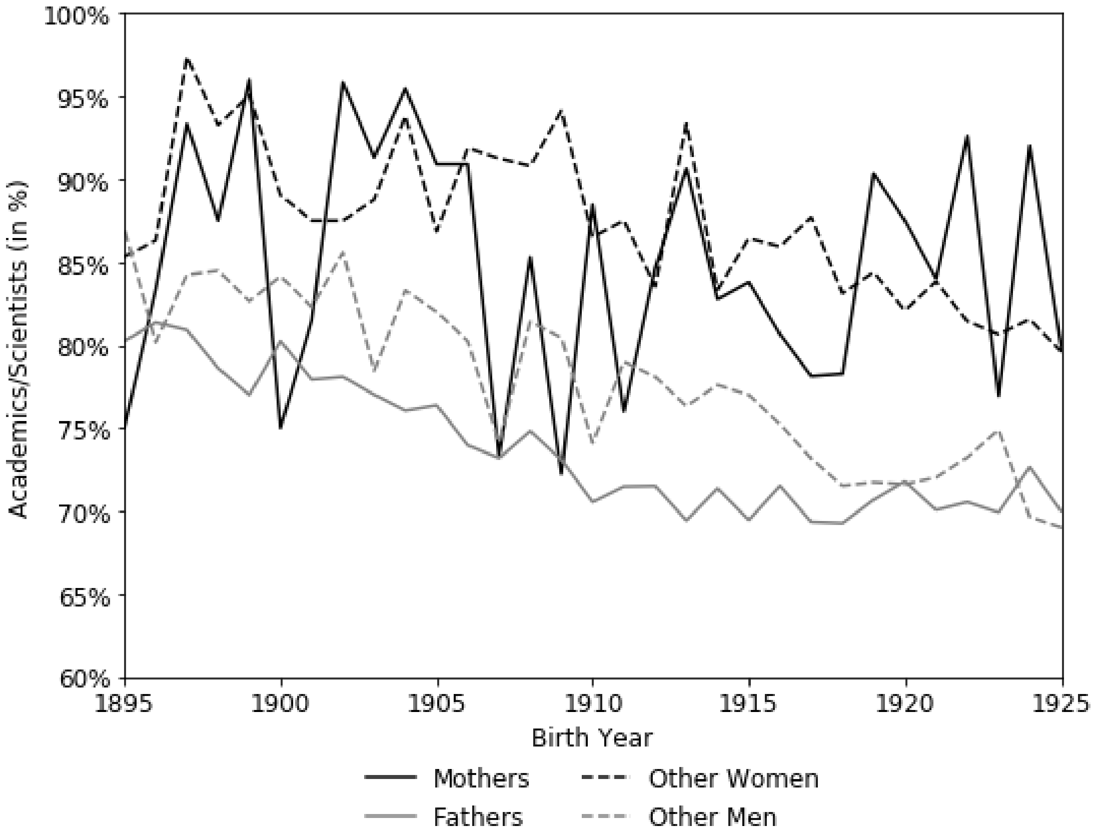


Notes: OLS estimates of β_s^d for demographic *d* (mothers, fathers, other women, and other men) in the regression:

$$y_{is}^{d} = \beta_s^d EventTime_i + \delta_t + \alpha_a + \mu_f + \epsilon_{it}$$

where y_{is}^{d} is the number of publications per scientist i (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; 202 of them are mothers, 1,272 other women without children, 17,280 fathers, and 6,265 other men.

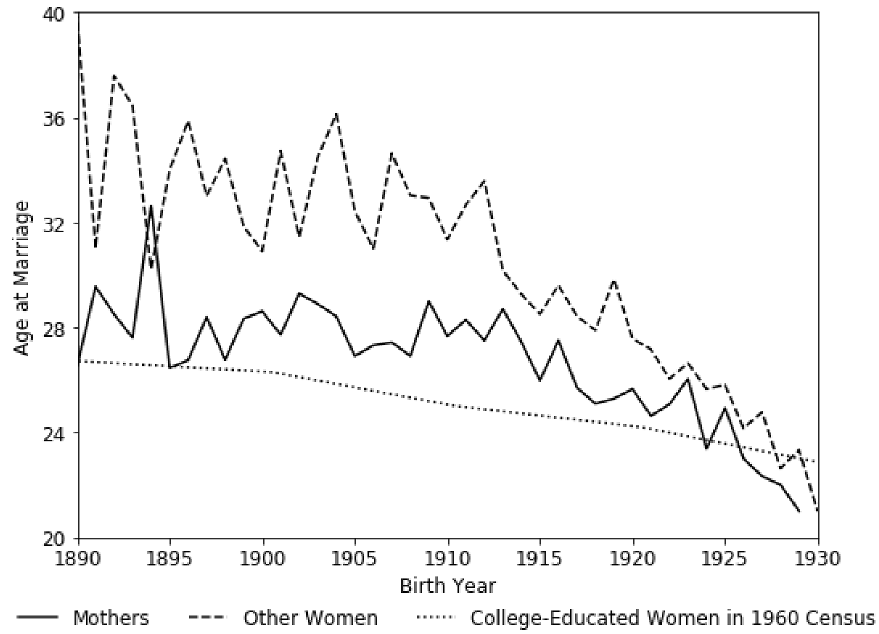
FIGURE A9 – PARTICIPATION IN ACADEMIA BY GENDER AND BIRTH YEAR



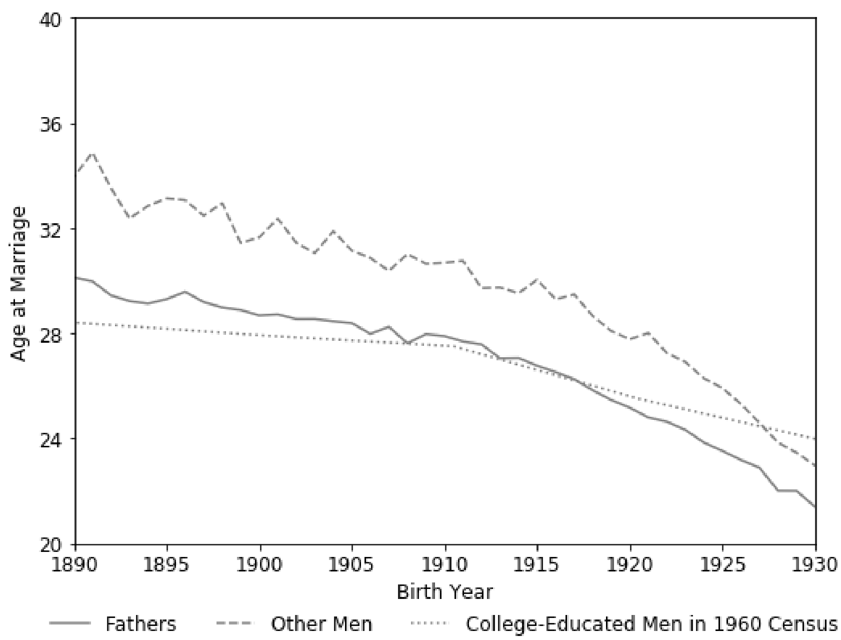
Notes: The share of scientists working in academia (measured by employment titles, including instructors, lecturers, professors) among all scientists. Data include 754 mothers, 2,783 other women, 36,140 fathers, and 13,269 other men who participated in academia and born between 1850 and 1940.

FIGURE A10 – MEAN AGE AT MARRIAGE BY BIRTH YEAR

PANEL A: WOMEN

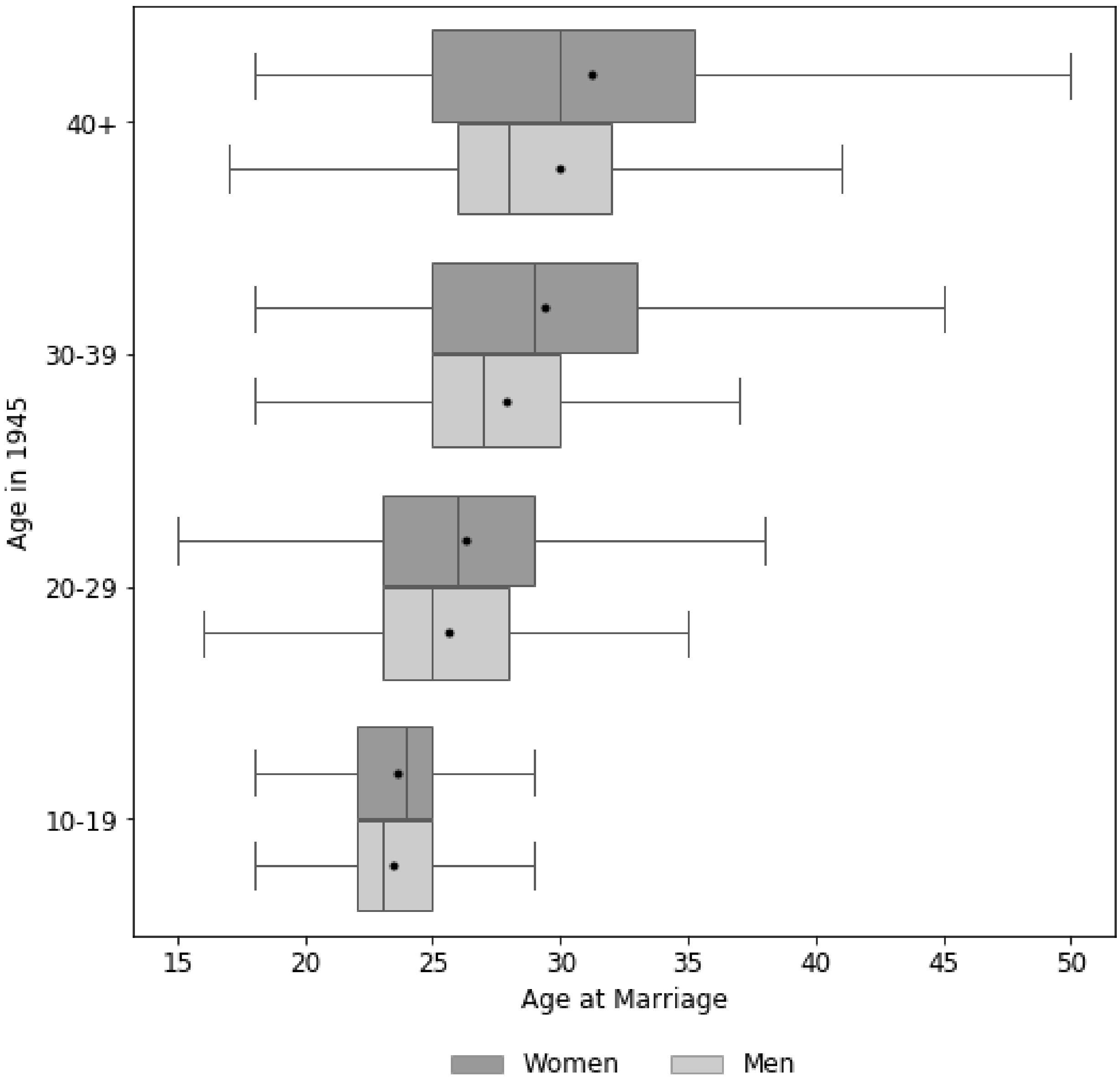


PANEL B: MEN



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.

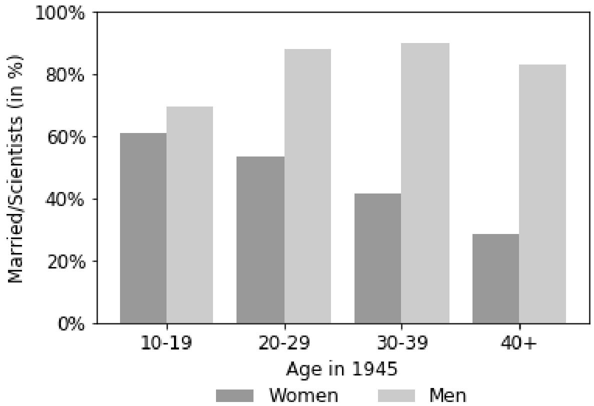
FIGURE A11 – AGE AT MARRIAGE BY BIRTH COHORT AND GENDER



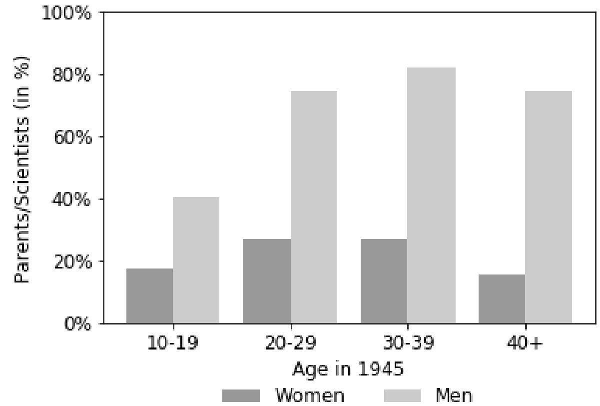
Notes: Mean and median ages at marriage for scientists across gender and birth cohorts. Birth cohorts are defined using the scientists' ages in 1945. We calculated each scientists age at marriage by subtracting their birth year from the year of their marriage. Both of these variables are reported in 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 A12 – SHARE OF MARRIED SCIENTISTS AND PARENTS,
AND NUMBER OF CHILDREN BY GENDER AND BIRTH COHORT IN THE PHYSICAL SCIENCES

PANEL A: SHARE OF MARRIED SCIENTISTS

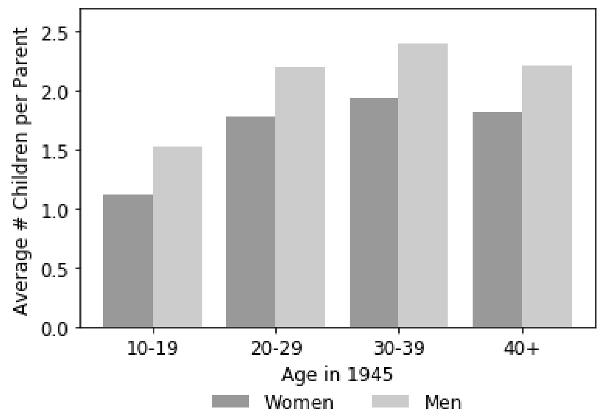


PANEL B: SHARE OF PARENTS



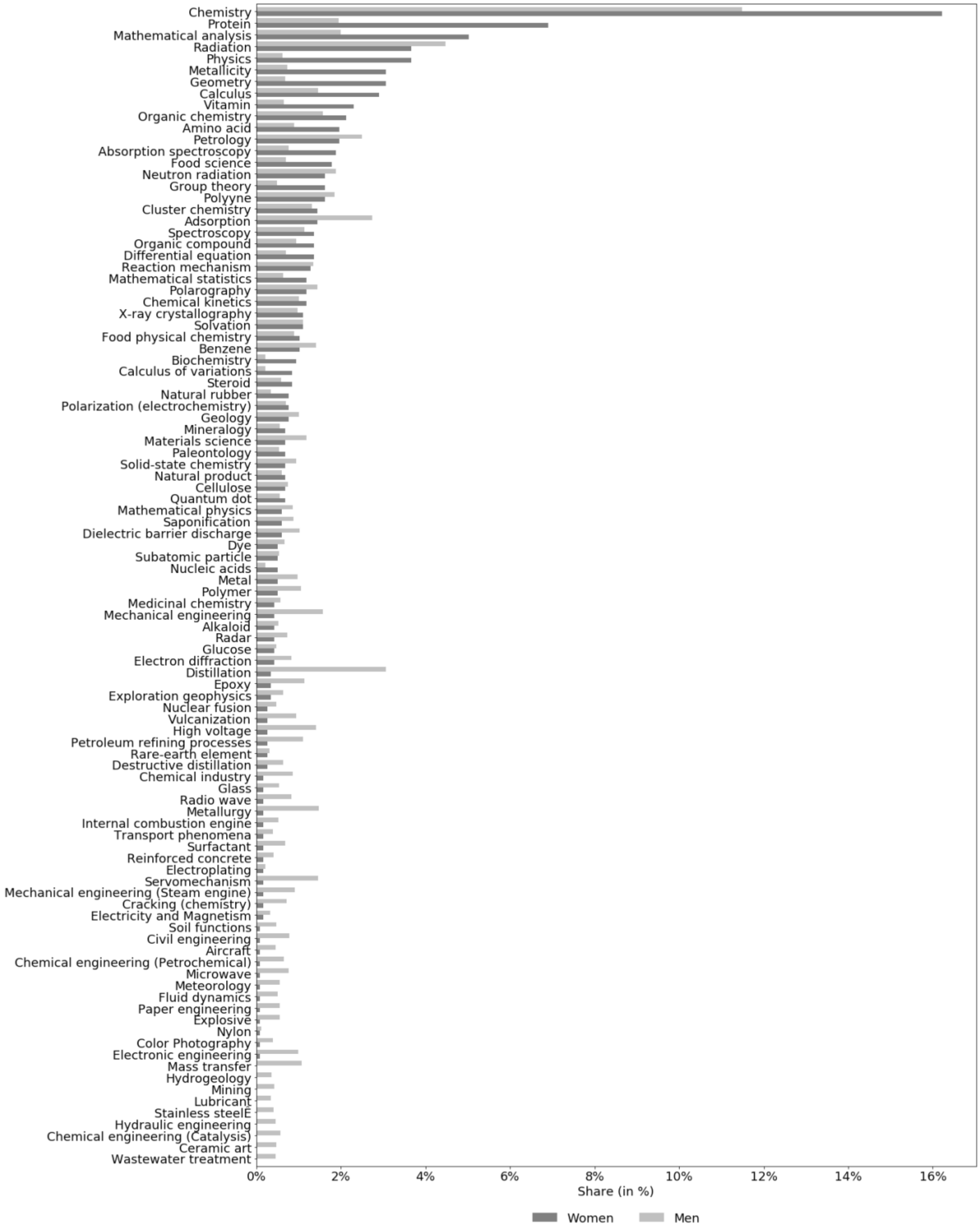
PANEL C: NUMBER OF CHILDREN PER SCIENTIST

PANEL D: NUMBER OF CHILDREN PER PARENT



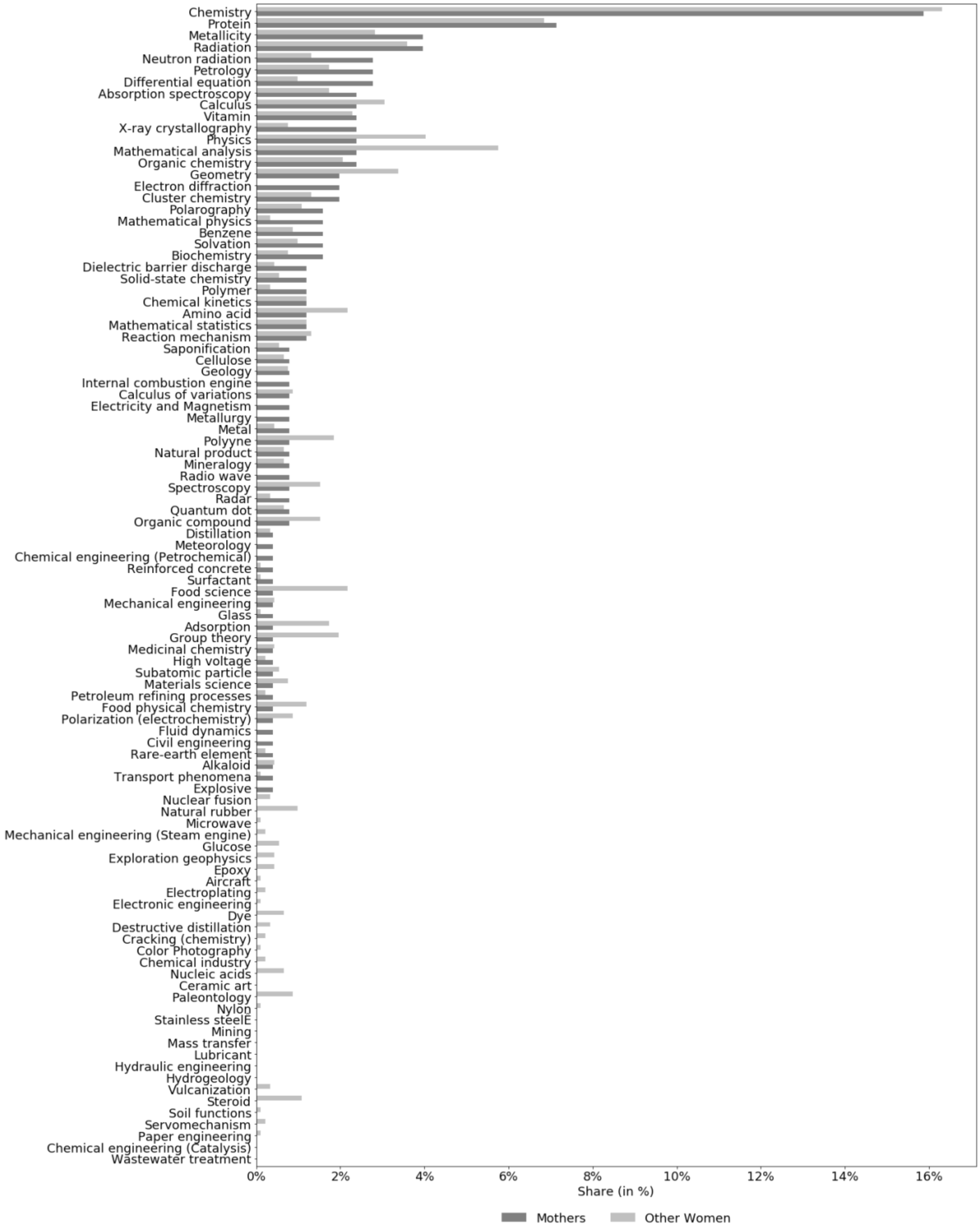
Notes: To investigate selection into marriage and parenting, we examine changes in the share of scientists who decided to marry and have children across birth cohorts, measured by their age in 1945, at the beginning of the baby boom (1946-1964). *Panel A* plots the share of scientists who were married. *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 A13 – 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 A14 – DISTRIBUTION OF SCIENTISTS ACROSS FIELDS: MOTHERS VS OTHER WOMEN

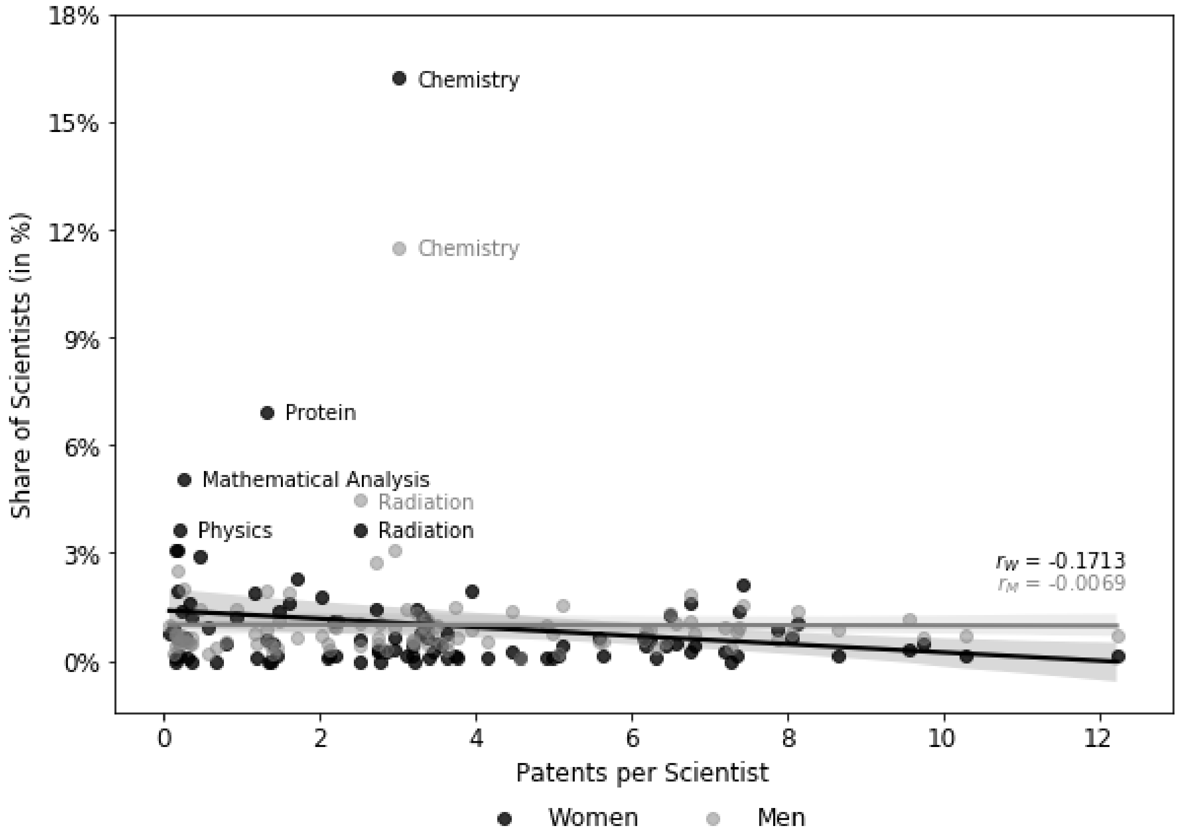


Notes: Share of female scientists across 100 fields, plotted separately for mothers and other women. Each scientist is assigned to a unique field, applying k-means clustering to information on their discipline and research fields (implementing an approach from Moser and San 2020).

FIGURE A15 – 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).

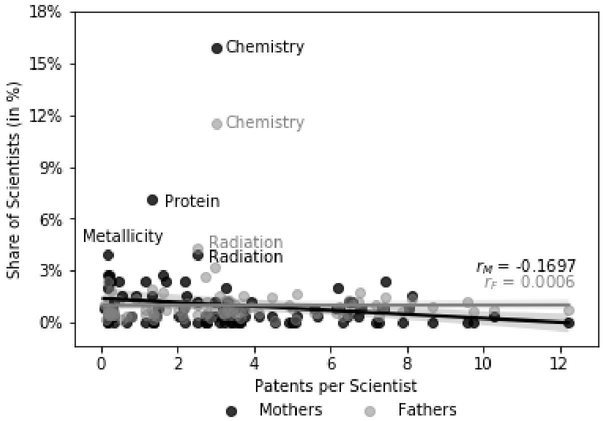
FIGURE A16 – FIELD DISTRIBUTION BY PRODUCTIVITY AND GENDER



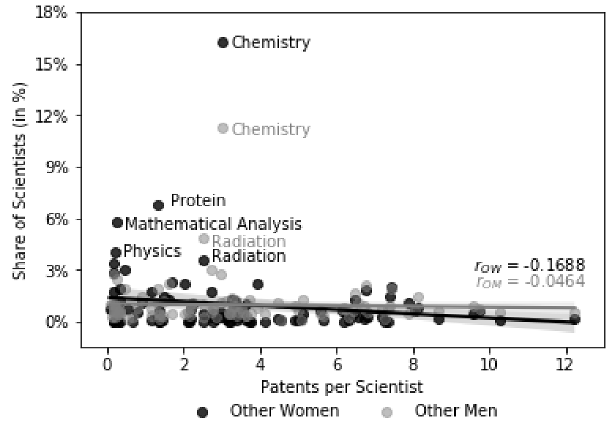
Notes: Share of scientists across 100 fields, plotted by patents per scientists per field and separately for women and men. Each scientist is assigned to a unique field, applying k-means clustering to information on their discipline and research fields (implementing an approach from Moser and San 2020).

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

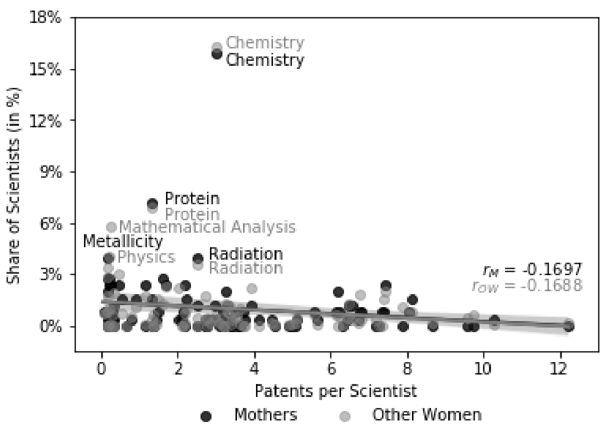
PANEL A: MOTHERS VS FATHERS



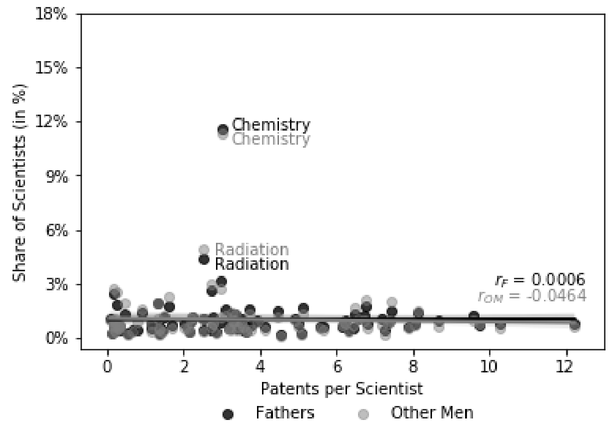
PANEL B: MEN VS WOMEN W/O CHILDREN



PANEL C: MOTHERS VS OTHER WOMEN



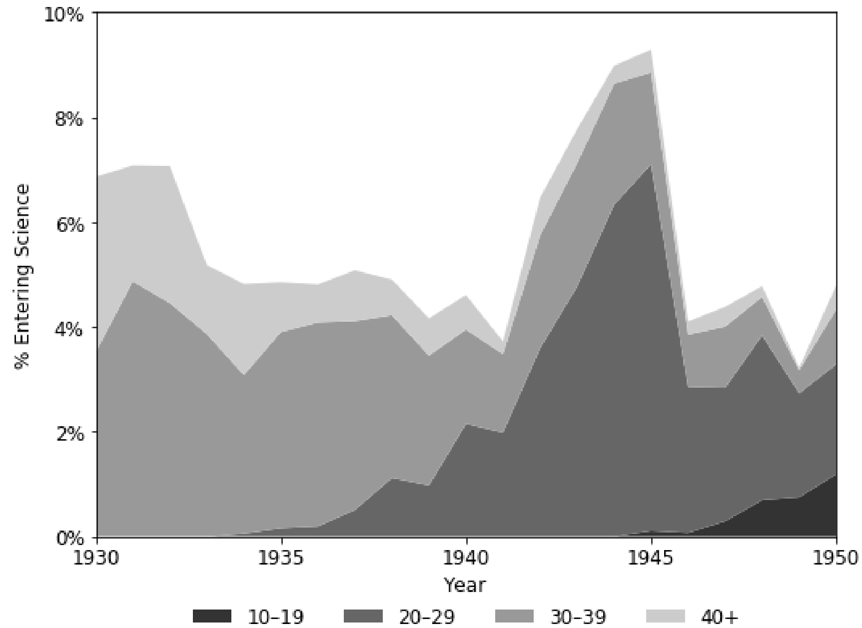
PANEL D: FATHERS VS OTHER MEN



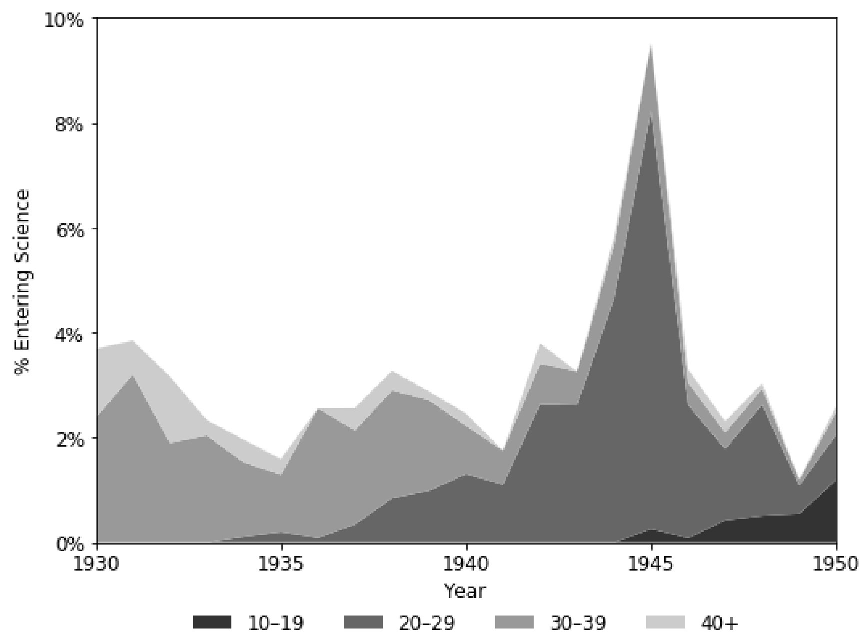
Notes: Panel A: Share of scientists across 100 fields, plotted by patents per scientists per field and separately for mothers and fathers. *Panel B:* Share of scientists across 100 fields, plotted by patents per scientists per field and separately for women and men who were not parents. *Panel C:* Share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