WOMEN IN SCIENCE
LESSONS FROM THE BABY BOOM

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PRELIMINARY AND INCOMPLETE
COMMENTS MUCH APPRECIATED!

How does parenting influence gender inequality in science? We investigate this question by examining data on children, productivity, and promotions for nearly 83,000 American scientists in 1956, the height of the baby boom (1946-64). Using patents to measure productivity, we find that parenting reduced the productivity of mothers but not fathers. Mothers were less productive in their 20s and early 30s but became more productive after age 35, reaching peak productivity several years after other scientists. Event study estimates show that the productivity of mothers declined after they married but recovered 15 years later. In contrast, fathers and other women were most productive in the early years after marriage. These differences in the timing of productivity have important implications for promotions. Specifically, we find that mothers were 21 percent less likely to be promoted to tenure compared with fathers and 19 percent less compared with other women. In contrast, fathers were slightly more likely to get tenure compared with other men. To interpret these findings, we investigate selection into marriage, parenting, and "survival" in science. Mothers were no less productive than other women, but female scientists married late and had fewer children than male scientists. Linking our data with faculty records, we show that female scientists, and especially mothers, were less likely to survive in science. Employment data reveal a dramatic decline in entry by women who were in their 20s at the baby boom, suggesting that the disparate burden of parenting created a lost generation of female scientists.

KEYWORDS: GENDER INEQUALITY, SCIENCE, CHILDREN, CHILD PENALTIES, AND BABY BOOM

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Women and minorities continue to be underrepresented in science. 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 they 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). Other potential factors include discrimination in hiring, glass ceilings in promotions (McDowell, Singell, and Ziliak 1999), and inequity in salary and support (Settles et al. 1996; Sonnert and Holton 1996).

Parenting is a possible cause of persistent inequality in science. Survey data indicate that women continue to carry a larger share of childcare responsibilities than men. According to the American Time Use Survey (2018), married mothers working full-time spent an average of 72 minutes per day caring for their children compared with 49 minutes per day for married fathers. In households where both spouses were working full time, mothers spent an average of 2.1 hours per day on cooking, cleaning, and other household chores, while fathers spent 1.4 hours. 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).

In this paper, we examine whether parenting – through its effects on productivity and promotions – helps to create gender inequality in science. Existing literature have found that parenting leads to gender inequality in *earnings* while evidence on *output* or *productivity* continues to be scarce. For instance, 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.[1] Survey data on MBA graduates indicate that nearly half of the earnings deficit for women can be explained by reduced weekly hours and no-work spells for women with children (Bertrand, Goldin, Katz 2010, p. 241).

To examine gender inequality in productivity and promotions, we exploit uniquely rich biographical data on 82,094 women and men who were active in American science in 1956 at the

[1] Klevens, Landais and Søgaard (2019) examining registry data for Denmark between 1980 and 2013. Extending that analysis to a broader set of six Scandinavian, English- and German-speaking countries, Klevens, Landais, Posch, Steinhauer, and Zweimüller (2019) show that mothers in the Scandinavian countries experience the smallest earnings penalties (21-26 percent 10 years after the birth of the first child), followed by 31 to 44 percent in the United States and the United Kingdom and capped by Austria and Germany with 51 to 61 percent.

height of the baby boom (1946-64). Using information on the year when a scientist married and on their number of children allow us to measure variation in family status. By matching scientists with their patents we can compare changes in productivity over the life cycle for male and female scientists with and without kids. To estimate the causal effects of starting a family on productivity, we estimate event studies of changes in patenting after marriage. Data on the scientists' university education and their career histories allow us to examine whether 1) mothers are less likely to enter tenure track positions compared with fathers and other women and 2) whether they are less likely to get tenure.

Examining productivity across the life cycle, we show that mothers are substantially less productive in their 20s and 30s, both compared with men and compared with other women. After age 35, however, mothers who were scientists became more productive, reaching peak productivity in the late 40s, nearly a decade after the peak for men.

Event studies of changes in patenting after marriage show that mothers became less productive in the first decade after they married, but then recovered dramatically 15 to 20 years after they married. 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. In contrast, women without children generate 5.0 additional patents in the first five years of their marriage but become less productive later. Importantly, there is no evidence that mothers are less productive than other women before marriage. The productivity of men (fathers and men without children) increases significantly for the first 10 years of their marriage but declines afterwards, even controlling for age.

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 to their entry in PhD programs. 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.

Women with PhDs, however, were less likely to get tenure-track jobs, especially if they had kids. Only 36 in 100 mothers with a PhD became assistant professors, compared with 45 fathers and other women (Table 3). Mothers who did become assistant professors took almost three times as long compared with fathers, taking an average of 4.4 years counting from the PhD, compared with 1.3 years for fathers and 2.8 years for other women. In fact, fathers were slightly more likely and quicker to become assistant professors compared with other men.

Female academic scientists with children were also less likely to get tenure compared with fathers and women without children. Only 27 percent of female academics with children achieved tenure, 21 percent less than fathers and 19 percent less than other women (48 and 46 percent, respectively).

A final section investigates selection into marriage, parenting, research fields, and into "survival" as a scientist. 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 the general population married two years earlier than men. We also find that women who did marry (and survived as a scientist) were almost twice as productive before age 27 (the median age of marriage for female scientists). For men, there are no productivity differences for scientists who married and those who did not. Matching our data with faculty directories we find that women were significantly less likely to survive as scientists compared with men.

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. BIOGRAPHICAL DATA ON FEMALE AND MALE SCIENTISTS

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.[2] 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.

[2] 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.

Detailed biographical data for 82,094 American scientists in 1956 allow us to examine US science at the height of the baby boom.[3] Beyond the Physical Sciences (volume 1), and the Biological Sciences (volume 2), the 1956 edition also includes the Social & Behavioral Sciences (volume III, 15,493 scientists). We use this disciplinary division to improve the patent matching.

Data in the MoS (1956) were subject to comprehensive input and review from "scientific societies, universities, colleges, and industrial laboratories." Jacques Cattell thanks them for having "assisted in supplying the names of those whom they regard as having the attainments required for inclusion in the Directory." He also thanks "thousands of scientific men who have contributed names and information about those working in science," and "acknowledges the willing counsel of a special joint committee of the American Association for the Advancement of 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.[4] 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

[3] 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).

[4] 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).

first names, which are rare both in the historical Social Security records and in our data. We create a separate algorithm to correct these names. 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.

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).[5]

2.1.3. Marriage and Children

A key advantage of the data for our project is that the MoS (1956) records the number of children for each scientist in 1956. For example, the entry for Dr. Giuliana C(avaglieri) Tesoro tells us that she was married in 1943 and had two children by 1956 (bold added for emphasis):

> 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.

[5] In addition to birth dates, the MoS (1956) also includes information on the place of birth for 99.5 percent of all 82,094 American scientists (working at US or Canadian institutions) in 1956, and 99.5 percent of 79,507 US scientists working at US institutions in 1956. These data allow us to separate US-born women and men in science from immigrants.

By contrast, an entry for Gertrude Belle Elion (Nobel Medicine 1988) shows no marriage and no children. According to her obituary, Elion remained unmarried after her fiancé died of endocarditis in 1941 and had no children.

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

Data on scientists' children is particularly valuable because it is impossible to get such data for the baby boom years from the US census data. Individual-level census records are only available until 1940, while we can observe children born until 1956. We do, however, match our scientists to the US census to obtain information on the birth year of children, and to perform event studies of the effects of parenting.

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).[6] 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).[7]

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.

[6] Undergraduate degrees include Bachelor of Science, Bachelor of Arts, Bachelor of Chemistry, and Bachelor of Education (Appendix Figure A1).

[7] 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).

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*:

> 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 Research 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).[8]

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.

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

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.[9] 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.

2.3.Matching Scientists with Census Records

Our main data include only the number of children that a scientist has, but not the year of when they were born. We therefore use the year of marriage to measure the year when scientists start their families and separately estimate changes in productivity after marriage for men and women without kids.

For supplementary analyses, we also match scientists with the 1940 US Census microdata to identify the birth year of each child and collect additional information on the scientist's family background. To match mothers with their census records, we first create a simple matching algorithm to identify individuals in the census 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.[10] Women are more difficult to match with the census than men because, among other things, they change their names upon marriage.

We manually match 227 of 892 scientists who are mothers with their records in the US census of 1940 (37.8 percent).[11] Of these women, 191 report having children living in the same household in 1940; another 2 report children living elsewhere.

We use census records in supplementary analyses to examine changes in productivity for fathers and mothers after the birth of a child. Matching mothers with their spouses further allow

[9] 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.

[10] 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.

[11] 451 of 892 mothers had not yet married in 1940; 352 of them were below 27, the median age at marriage for female scientists.

us to directly 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 (through family members or servants) helped to lessen the burden of parenting on scientists.

III. GENDER DIFFERENCES IN PRODUCTIVITY

To investigate gender inequality, and specifically, a potentially unequal impact of childbearing on science, we first examine differences in patenting across men and women with and without children. Next, we investigate changes in patenting over the life cycle of male and female parents compared with other scientists. Finally, we present event study estimates of changes in productivity after marriage for male and female parents, compared with other scientists.

3.1. Cross-Sectional Analyses of Productivity

First, we compare differences in productivity across men and women with and without kids. Summary statistics indicate that women scientists were much less likely to become inventors (Table 1). Just 3.4 percent of female scientists had submitted at least one successful patent application, compared with 22.3 percent of men.

Differences in the rate and intensity of invention between mothers and other women were small. Compared with other women, mothers were less likely to have any patents (with shares of 3.1 and 3.5 percent, Table 1) but they had more patents on average (with 0.19 and 0.16 patents per scientist, respectively).

Notably, fathers were significantly more productive than other men. 23.8 percent of fathers produced at least one patent, compared with 18.3 percent of other male scientists (Table 1). The average father produced 2.14 inventions, 45.6 percent more compared with 1.47 patents for other male scientists.

OLS estimates gauge gender differences in productivity controlling for differences over time, across birth years, and across fields. Specifically, we estimate

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

where the dependent variable y_{it} counts US patents per scientist i (multiplied by 100) in year t. The variable $Parent_i$ indicates scientists who were parents in 1956, $Female_i$ indicates scientists who are women, and $Female * Parent_i$ indicates scientists who are mothers; δ_t are year fixed effects (to control for changes in patenting 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 across fields *f* (e.g., across theoretical fields, like mathematical analysis, in which few scientists patent, and applied fields, like chemical engineering.

OLS estimates confirm that female scientists patented much less than men. 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). This later result may be due to selection if only exceptionally productive mothers survived in science. We examine such selection below. All results are robust to controlling for scientist age fixed effects (column 2, replacing cohort fixed effects), extending the data to include older scientists up to age 80 (column 3) and to including all scientists in the physical, biological, and physical sciences (columns 4-5).

Estimates also corroborate that fathers were more productive compared with other men. Male scientists with children produced 1.772 additional patents per 100 scientist and year (Table 2, column 1, significant at 1 percent), equivalent to 20.1 percent more compared with the mean. Intensity estimates taking into account the *number* of children per scientist (Appendix Table A2, suggest that the productivity of women suffered most with the first child, while fathers became more productive with each child.

Connecting our results on productivity with existing research suggests that differences in productivity may help explain differences in earnings between married and single men. Examining earnings in manufacturing, Goldin (1990, p. 102) shows that married men earned 17 percent more historically compared with single men, while there was no difference for married and single women. Notably, this marriage premium for men has remained stable since the 1890s (Goldin 1990, p. 91). Using data for the late 20$^{\text{th}}$ 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. Examining data on earnings of MBA graduates between 1990 and 2006, Bertrand, Goldin, and Katz (2010) show that male MBAs with children have earnings that are 18 log points higher than childless men. While women's earnings decline sharply around three to four years after the birth of their first child (Bertrand et al. 2007, 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.

3.2. Differential Changes in Productivity Across the Life Cycle of Scientists

Comparing changes in productivity across the life cycle shows that mothers are less productive in their 20s and 30s relative to both fathers and other women without children. The On average, scientists who are mothers produce no patents between the ages of 20 and 24 and just 1.4 patents per 100 scientists and year between the ages of 25 and 29.

Yet, mothers' productivity increased in their 30s and 40s to peak at age 42 (with 7.0 patents per year of age and per 100 scientists; Figure A2, Panel A) long after the productivity of other scientists had peaked. Mothers produce 2.2 patents per 100 scientists and year between the ages of 30 and 34, 2.3 patents between 35 and 39, and 4.0 between 40 and 45. Mothers continue to be productive in their 40s, producing 3.3 patents per year and 100 scientists between 45-50

This late boost in productivity is unique to mothers. For women without children, productivity peaks at age 30 (with 3.8 patents per year of age and per 100 scientists; Figure A2, Panel B). For fathers, productivity peaks at age 37 (with 18.4 patents per 100 scientists and year, Figure A2, Panel A), one year before the peak productivity of other men (15.9 patents at age 38, Figure A2, Panel B).

To investigate changes in patenting across the life cycle 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 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 (the excluded age). 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 kids), 25,829 fathers, and 8,367 other men.

Age-specific estimates of β_a^{om} indicate confirm that men without children become more productive until their late 30s and decline afterwards (Figure 2). Patenting levels of these men increase steadily from 0.26 additional patents at age 18 (relative to patenting levels at age 20) to a peak of 14.0 additional patents at age 38. Starting in their late 30s, men without children patent less and their productivity declines to 10.7 additional patents at age 40, 10.3 additional patents at age 45, 6.0 additional patents at age 50, and 3.4 additional patents at age 55, 0.42 additional patents at age 60 (not statistically different from zero), and 1.2 fewer patents at age 65 (not statistically different from zero).

Analogous estimates of β_a^f show that fathers (*parents* who are not *female*) also become more productive into their late 30s and slow down afterwards. Fathers' productivity, however, peaks slightly earlier than that of other men, with 16.5 additional patents at age 35. Starting in their late 30s, fathers patent less and their productivity declines to 15.8 additional patents at age 40, 10.6 additional patents at age 45, 7.5 additional patents at age 50, 4.2 additional patents at age 55, 2.0 additional patents at age 60, and 1.1 fewer patents at age 65 (not statistically different from zero).

Women without children become more productive earlier on in their late 20s and slow down afterwards, although at a slower pace than men. β_a^{ow} estimates for these women show their patenting levels peak from 0.07 fewer patents at age 18 (relative to patenting levels at age 20) to 3.8 additional patents at age 30. Patenting levels of mothers without children persist at similar levels throughout their 30s and even their 40s to 2.5 additional patents at age 35, 2.7 additional patents at age 40, and 3.0 additional patents at age 45, but begin to decrease in their 50s to 1.2 additional patents at age 50 (not statistically different from zero), 0.49 additional patents at age 55 (not statistically different from zero), 0.16 additional patents at age 60 (not statistically different from zero), and 0.22 additional patents at age 65 (not statistically different from zero).

Notably, mothers are less productive in their 20s and early 30s, but then accelerate after age 35 and reach peak productivity several years after the productivity of other scientists has declined. Documenting the exceptional productivity of this group, estimates for β_a^m begin at 0.21 fewer patents at age 18 and increase to a relative peak of 4.0 additional patents at age 27 before decreasing to 2.7 additional patents at age 30 and 2.0 additional patents at age 35. However, mothers' inventive activity slowly recovers in later years to 3.9 additional patents at age 40 and a peak of 6.5 additional patents at age 42 before slowly declining to 3.6 additional patents at age 45, 0.19 fewer patents at age 50, 0.66 additional patents at age 55, 0.16 additional patents at age 60, and 1.4 fewer patents at age 65.[12]

3.3. Event Studies of Changes in Productivity after Marriage

Changes in productivity across the life cycle suggest that mothers are less productive in their 20s to early 30s when many of them are taken care of young children. We now test whether mother's reduced productivity in those years may be due to the disparate burden of parenting. An ideal experiment to measure the causal effects on output would randomly assign scientists to parenting. In the absence of such an experiment, we estimate an event study of marriage as a proxy for the birth of the first child. During the period that we examine, parents typically had their first child soon after they married (Weiss 2020, p. 4). We exploit this fact to estimate separate regressions of changes in productivity after the year of marriage for mothers, fathers, and other women and men without children.

Empirically, the event study approach takes advantage of share changes in productivity around the year of marriage for mothers relative to fathers. While a scientist's choice to have children may not have been exogenous; the event of marriage (and the birth of the first child) creates a sharp change in productivity, which is arguably orthogonal to unobserved determinants of productivity that evolve more smoothly over time. Another benefit of the event study is that it allows us to trace out the long-run trajectory of productivity relative to the year of after marriage.

Event studies estimate OLS regressions

$$y_{iy}^d = \beta_y^d EventTime_i + \delta_t + \alpha_a + \mu_f + \epsilon_{it} \quad (3)$$

where y_{iy}^d is the number of US patents per scientist i (multiplied by 100) of demographic d (mothers, fathers, other women, and other men) in year y relative to the year before marriage. The coefficient β_y^d is a vector of time-varying estimates of inventions in year y by scientists of

[12] Due to the small number of observations, these estimates are not significant at the 5 percent level, except at ages 32 and 34.

demographic *d* compared with scientists in the same demographic one year before marriage (the excluded year). Omitting the event time dummy at *y = -1* implies that the event time coefficients β_y^d estimate the impact of children relative to the year just before the year of marriage. Age fixed effects α_a control for variation in patenting across the life cycle of scientists. Year dummies and other variables are defined as above. We are able to identify the effects of age, year, and event time dummies because, conditional on age and year, there is variation in event time driven by variation in the age at which scientists get married.

Event study estimates of β_y^f show that fathers (*parents* who are not *female*) become significantly more productive in the first 10 years of marriage (Figure 3). Compared with their own output in the year immediately preceding their marriage, fathers' productivity increases to 4.0 additional patents 5 years after marriage and a peak of 5.6 additional patents 9 years after marriage. Interestingly, the productivity of fathers begins to decline after the first decade of marriage with 3.5 additional patents after 15 years and 1.1 additional patents after 20 years (not statistically different from zero) and 0.52 fewer patents 30 years after marriage (not statistically different from zero).

Event-study estimates for other men (β_y^{om}) follow a similar pattern over time, with an increase immediately after marriage, a productivity peak around 10 years into their marriage, and a steady decline afterwards.

In sharp contrast to fathers, the productivity of mothers declines immediately after they marry, stays low for the first 15 years, but then *increases* at a time when the output of all other demographic groups declines. Estimates of β_y^m begin at 0.51 fewer patents in the year of marriage (relative to the year immediately before the marriage), and persist at low levels for the first 15 years after marriage. At that time, however, mothers' productivity increases to 6.8 additional patents 20 years after marriage and 6.9 patents 22 years after marriage. Mothers remain productive at that time, with 6.2 additional patents 25 years after marriage, and 5.0 additional patents 30 years after marriage, exceeding the estimates of all other demographic groups.

Estimates for other women (β_y^{ow}) remain close to estimates for mothers for the first 15 years, albeit with higher productivity in the early years of marriage. 15 years into the marriage though, productivity trends for other women are similar to those for men, while mothers' productivity increases.

IV. Gender Differences in Promotions

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. 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.[13]

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 1) the transition from undergraduate to PhD 2) PhD to assistant professor and 3) assistant professor to tenure. In addition to documenting differences in the rate of promotions, we examine differences in the *speed* of promotions. Data on academic promotions show that women, and especially mothers, take a lot longer to get tenure starting from their undergraduate degree (Appendix Figure A3).

4.1. 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 to be disadvantaged in promotions, they have weaker incentives to pursue a PhD.

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

[13] 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.

you'll get married, and you'll have kids, and what good will a PhD have done?" (Lucci-Cannapiri 2019).[14]

Yet, we find that 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 (Appendix Figure A4). This is consistent with a labor market that discriminates against women, requiring them to get better credentials than men to do the same job. Women also faced many formal and informal barriers that discouraged them to pursue PhDs.

Parents of both genders were less likely to have a PhD: 83 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.

4.2. 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, and most of them remained instructors for their entire careers. By comparison, 44.6 percent of other women 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 A5). 84.5 percent of mothers became academic scientists compared with 73.9 percent of fathers and 88.6 percent of other women (Table 3).[15]

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

[14] 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).

[15] 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).

slightly more likely to become assistant professors compared with other men and they advanced more quickly.

4.3. Mothers Were Less Likely to Get Tenure

Mothers were also much less likely to get tenure. Just 27 percent of female academic scientists with children achieved tenure, compared with 48 percent of fathers and 46 of other women (Table 3). Since tenure is time-constrained, mothers who did not get tenure within the first five years after landing an assistant professor job were unlikely to attain it (Figure 5). Yet, more mothers than any other scientists achieved tenure 10 to 20 years after starting as an assistant professor. These patterns are consistent with the marked productivity increase for mothers at a later age in the patent data. The median mother is 43 years old when she has been an assistant professor for 10 years. At that time, mothers continue to be near peak productivity, while men and other women have already declined significantly (Figure 2).

In contrast, fathers were slightly more likely to get tenure than other men: 48 percent of fathers got tenure, compared with 47 percent of other men. Fathers also advanced slightly more quickly: 44 in 100 fathers who were assistant professors attain tenure within 5 years of becoming an assistant professor, compared with 42 other men. These comparisons suggest that the tenure penalties for parenting fell squarely on mothers.

V. Selection

We have found that mothers are less productive compared with both fathers and childless women in their 20s and early 30s, but then experience a boost in productivity in their late 30s and early 40s. Moreover, event study estimates have shown that mothers are less productive in the first 15 years after marriage (when their children are young), but then experience a boost in productivity afterwards while other scientists decline. Could this differential pattern of productivity across the life cycle and after marriage be due to selection? To help answer this question, we investigate selection into marriage, parenting, research fields, and “surviving” in academic science.

5.1. Selection into Marriage

Importantly, we uncover no evidence that female scientists who chose to have children were less productive than other female scientists. Comparing married women with and without children suggests that mothers were no less productive than other married women before they married. Mothers were almost half as likely to have patented before the age of 27 compared with other married women. 6.8 percent of married women had at least one patent by age 27 compared with just 3.5 percent of other women.[16] Women who became mothers were slightly less likely to have at least 1 patent (3.1 compared with 3.5 percent), but they also produced more patents on average than other women (with 19 patents per scientists, compared with 16, Table 1).

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 6, 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 A6). 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 A7). Women in the oldest cohort (40 and above in 1945) married at a median age of 30 (and an average of 31.2, Appendix Figure A7), 2 years after 28, the median age of marriage for men (an average of 30.0). Among the baby boom parents,

[16] 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.

women married at a median age of 26 (and an average of 26.3), 1 year after the median age at marriage for men (25 years and an average of 25.6).

5.2. Selection into Parenting

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 6, Panel A). 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.[17]

Female scientists also had many fewer children, with 0.41 children per female scientist, compared with 1.69 per male scientist (Figure 6, Panel C). Conditional on having any children, men had 2.3 compared with 1.9 for women (Figure 6, 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 6, Panel C). Male scientists always had between 1.6 to 1.7 children with minimal changes over time.

Investigating differences in productivity *before marriage* we find that mothers were slightly less likely to have patented than other women but had more patents on average. 4.3 percent of mothers had patented by age 27 compared with 5.1 percent of other women. Differences in pre-marriage patents for fathers and other scientists are minimal, with fathers having slightly more patents (9.3 patents) at age 27, compared with other male scientists (9 patents).

[17] 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.

5.3. 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 may select into research fields that were less competitive (Niederle and Vesterlund 2007)[18] 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, compared with 0.6 percent of men (Appendix Figure A9). 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).[19]

There do not appear to be notable 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

[18] 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.

[19] 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).

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).

5.4. Selection into "Surviving" as a Scientist

To investigate whether women (and especially mothers) had to be exceptionally talented to survive in STEM, we digitized the faculty records of Columbia University from 1943 to 1945 to capture pre-baby boom stock of scientists at a major university. We then use a combination of algorithmic and manual matching to check which scientists (who were still of working age, below 65 in 1956) were recorded in the MoS (1956).[20]

These data indicate that women were substantially less likely to survive in science compared with men. Among 387 women who were on the faculty at Columbia from 1943 to 1945, only 11.9 percent survived to enter the MoS in 1956 (Table 4). By comparison, male faculty members at Columbia were 7.6 percent more likely to survive to enter the MoS in 1956; 19.5 percent of 1,735 male professors at Columbia in 1943 to 1945 were recorded in the MoS (1956).

Information on parents in the MoS indicate that the surviving scientists were less likely to be mothers. 11 of the 46 surviving female scientists were mothers (23.9 percent) and 255 (75.2 percent) of the 339 surviving male scientists were fathers (Table 4).[21]

[20] Among 2,446 faculty members at Columbia University in 1943 to 1945 387 were women (18.2 percent) and 1,735 were men (81.8 percent). For the remaining 324 scientists (13.2 percent), gender is unknown. Using first, middle, and last names, we can match 478 scientists who were active at Columbia in 1943 to 1945 to the MoS in 1956. Of these 478 scientists, 385 report Columbia as their employer for 1943 to 1945.

[21] Due to the small number of surviving scientists we cannot determine whether scientists who survived were more productive. Instead, we are in the process of estimating instrumental variable regressions, using predicted parental status for scientists of a specific gender and birth cohort to investigate selection.

VI. 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.[22] 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.

6.1. 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 A10, Panel A).[23] 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 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.

6.2. 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 7). 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.

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[22] 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).
[23] 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*.

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

VII. 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.

References

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

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

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

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

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

Blau, Francine D., Patricia Simpson, and Deborah Anderson, 1998. "Continuing Progress? Trends in Occupational Segregation Over the 1970s and 1980s." *Feminist Economics*, 4(3), pp. 29-71.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, 2017. Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, *132*(2), pp. 665-712.

Kulis, Stephen, Diane Sicotte and Shawn Collins. 2002. "More than a pipeline problem: Labor supply constraints and gender stratification across academic science disciplines." *Research in Higher Education*, 43(6), pp. 657-690.

Levenshtein, Vladimir, 1966. "Binary codes capable of correcting deletions, insertions, and reversals." *Soviet Physics Doklady*. 10 (8), February, pp. 707-10.

Lucci-Canapari, Jeanna. 2019. "Special Symposium Honors Steitz, Illuminates Challenges that Women Scientists Face" Yale School of Medicine, Press Release, March 18.

McDowell, John M., Larry D. Singell, and James P. Ziliak, 1999. "Cracks in the Glass Ceiling: Gender and Promotion in the Economics Profession." *The American Economic Review*, 89(2), pp. 392-396.

Moser, Petra, 2012. "Innovation without Patents – Evidence from World's Fairs." *The Journal of Law and Economics*, Volume 55, No. 1, February 2012, pp. 43-74.

Moser, Petra and Shmuel San, 2020. "Immigration, Science, and Invention. Lessons from the Quota Acts." Working paper, New York University.

Mundy, Liza. 2017. *Code Girls. The Untold Story of the American Women Code Breakers of World War II.* New York: Hachette Books.

National Academy of Science. 2006. *Beyond Bias and Barriers: Fulfilling and Potential of Women in Academic Science and Engineering.* Washington DC: National Academies Press.

National Science Foundation, Arlington, Va. Div. of Science Resources Statistics. 2002. *Women, minorities, and persons with disabilities in science and engineering.* Available at https://www.nsf.gov/statistics/women/.

Nelson, Donna and Diana Rogers. 2004. *A national analysis of diversity in science and engineering faculties at research universities.* University of Oklahoma, Department of Chemistry.

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

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

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

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

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

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

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

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

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

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

Waldrop, M. Mitchell. "Why we are teaching science wrong, and how to make it right." *Nature*. 523 (7560), pp. 272–274.
Weiss, Jessica. 2000. *To Have and to Hold. Marriage, the Baby Boom & Social Change.* Chicago and London: The University of Chicago Press.
Winkler, William E. 2006. "Overview of Record Linkage and Current Research Directions." US Census, Research Report Series, RRS.

TABLE 1 – COMPARISON OF MEANS FOR WOMEN AND MEN

	Women	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%	-	-	-	-
N children	0.41	1.69	1.88	0.0	2.28	0.0
	(0.88)	(1.35)	(0.89)		(1.05)	
Share inventors	3.4%	22.3%	3.1%	3.5%	23.8%	18.3%
N patents	0.16	1.97	0.19	0.16	2.14	1.47
	(1.95)	(8.71)	(3.09)	(1.47)	(9.31)	(6.69)

Notes: Comparisons of means for 70,230 American scientists in the MoS (1956). The share of married scientists *(Share married)* includes scientists who reported their year of marriage. *Age at marriage* scientist is calculated by subtracting the scientist's birth year from their year of marriage. The *Share parents* measures the share of scientists with at least one child in 1956; # Children reports the number of children per scientist. The *Share patentees* is the number of scientists with at least one patent divided by the total number of scientists.

TABLE 2 – EFFECTS OF PARENTING ON THE PRODUCTIVITY OF MALE AND FEMALE SCIENTISTS, US PATENTS 1930-70

	Patents per 100 scientists per year				
	(1)	(2)	(3)	(4)	(5)
Female	-5.870***	-5.627***	-5.245***	-4.108***	-3.730***
	(0.173)	(0.174)	(0.156)	(0.068)	(0.061)
Parent	1.772***	1.898***	1.675***	1.606***	1.495***
	(0.135)	(0.138)	(0.125)	(0.068)	(0.062)
Female*Parent	-0.912**	-1.090***	-1.293***	-1.548***	-1.614***
	(0.389)	(0.391)	(0.366)	(0.123)	(0.114)
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	Physical sciences	Physical sciences	Physical sciences	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

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 $y_{it} = \beta_1 Parent_i + \beta_2 Female_i + \beta_3 Female * Parent_i + \delta_t + \pi_b + \mu_f + \epsilon_{it}$, 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, $Female_i$ indicates scientists who are women, and $Female * Parent_i$ indicates scientists who are 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*. Column (2) replaces birth cohort fixed effects from Column (1) with age fixed effects. Column (3) extends Column (1)'s estimates to scientists who in ages 18-80. Columns (4)-(5) serve as robustness checks for columns (1)-(3) respectively by including scientists in all volumes within the MoS (1956). "All" disciplines include the physical, biological, and social sciences.

TABLE 3 – COMPARISON OF MEANS FOR WOMEN AND MEN IN ACADEMIA

	Women	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 academic	87.7%	74.6%	84.5%	88.6%	73.8%	77.1%
Share PhD	84.1%	77.5%	83.2%	84.4%	76.6%	79.8%
Share assist. prof.	42.7%	45.5%	35.9%	44.6%	45.4%	45.9%
Share tenured	41.7%	47.7%	26.8%	45.7%	47.8%	47.2%

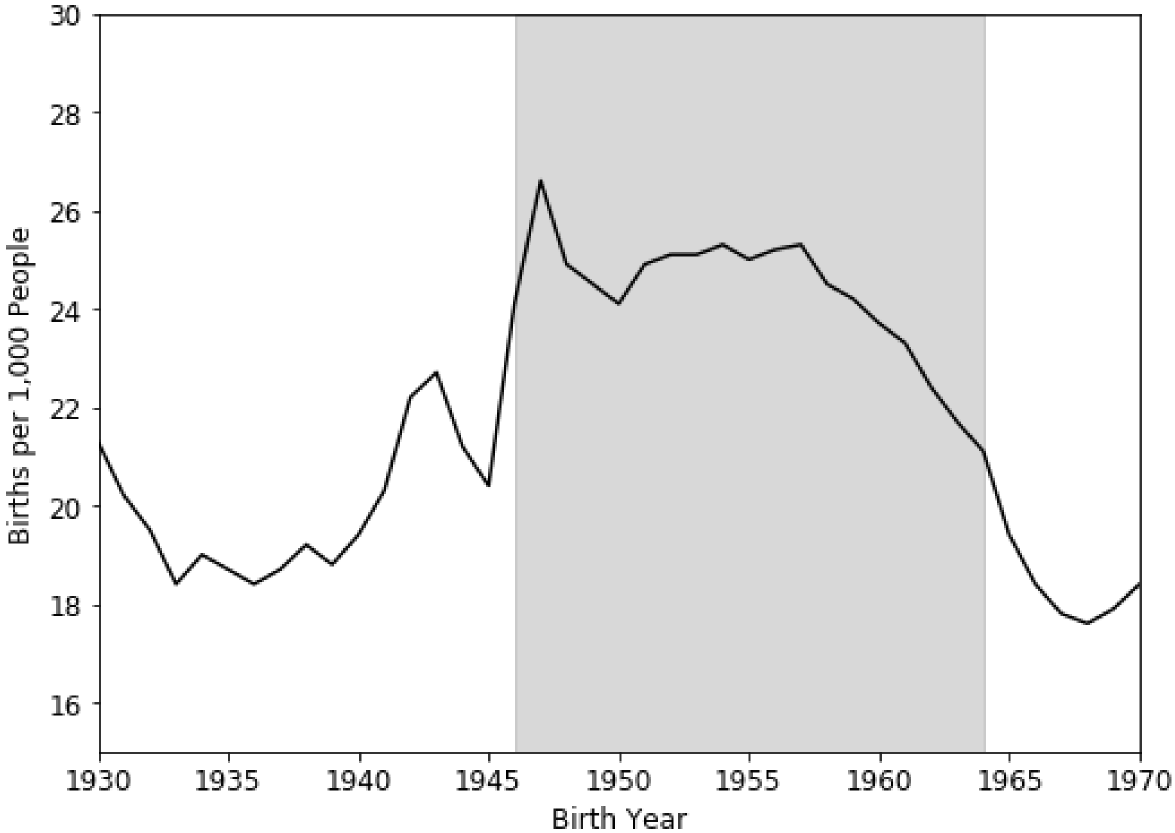
Notes: Comparisons of means for 70,230 American scientists in the MoS (1956). *Share academic* divides the number of scientists who held a job in academia at least once by the total number of scientists. *Share PhD* divides scientists with PhDs by the total number of academic scientists. *Share assist. prof.* represents the share of academic scientists who worked as an assistant professor at least once (excluding visiting assistant professors). *Share tenured* measures the share of academic scientists who worked as an associate or (full) professor (excluding visiting associate and full professors) at least once.

TABLE 4 – COMPARISON OF MEANS FOR WOMEN AND MEN AT COLUMBIA IN 1943-1945

	Women	Men	Women		Men	
			with children	w/o children	with children	w/o children
Panel A – Faculty at Columbia in 1943-45						
N Columbia faculty 1943-5	387	1,735	-	-	-	-
Panel B – Surviving Columbia Faculty in MoS (56)						
N Columbia faculty in MoS 56	46	339	11	35	255	84
Share (in %)	11.9%	19.5%	-	-	-	-
Age in 1956	54.5	55.6	49.82	56.1	55.1	56.8
	(8.80)	(11.24)	(9.93)	(7.92)	(11.04)	(11.81)
Share married	39.1%	78.2%	90.9%	22.9%	89.4%	44.0%
Age at marriage	27.9	29.8	26.3	29.9	29.0	34.2
	(6.19)	(6.47)	(5.79)	(6.47)	(5.65)	(9.03)
N children	0.48	1.72	2.00	0.0	2.29	0.0
	(0.96)	(1.30)	(0.89)		(0.98)	

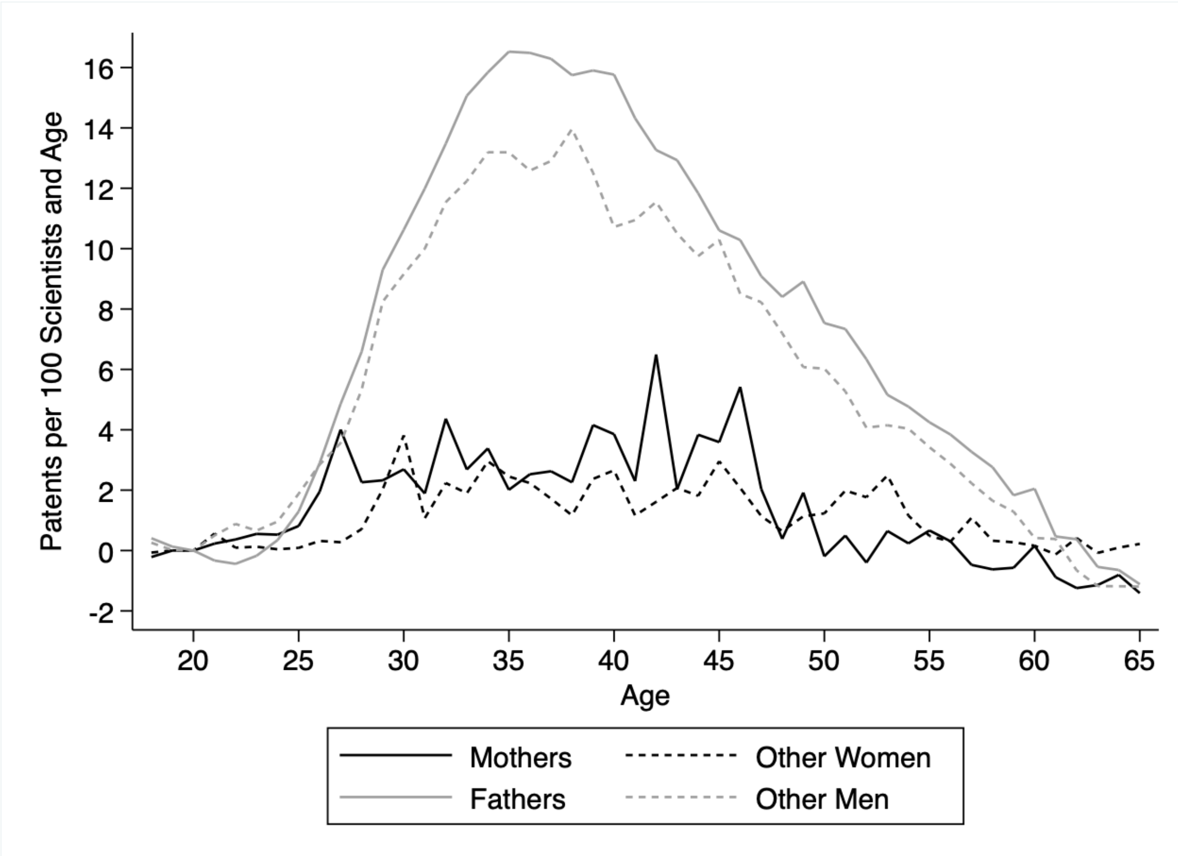
Notes: Comparisons of means for 385 American scientists in both the MoS (1956) and the Columbia University catalogue for 1943-1945. The share of married scientists *(Share married)* includes scientists who reported their year of marriage. *Age at marriage* scientist is calculated by subtracting the scientist's birth year from their year of marriage. # Children reports the number of children per scientist. The *Share patentees* is the number of scientists with at least one patent divided by the total number of scientists.

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



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), 25,829 fathers, and 8,367 other men.

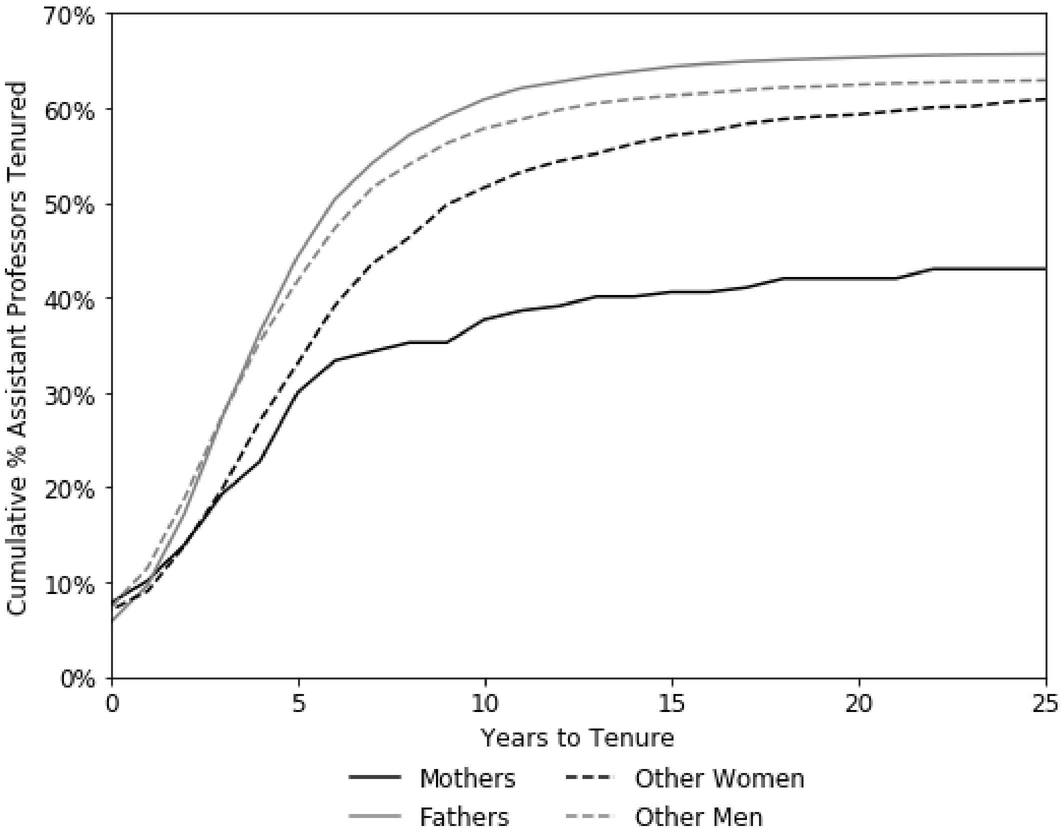
FIGURE 3 – EVENT STUDY ESTIMATES OF CHANGES IN PRODUCTIVITY AFTER MARRIAGE

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

$$y_{iy}^d = \beta_y^d EventTime_i + \delta_t + \alpha_a + \mu_f + \epsilon_{it}$$

where y_{iy}^d is the number of patents per scientist i (multiplied by 100) of demographic d in year relative to marriage *y*. Productivity is measured by patents in year *y* after marriage per 100 scientists in demographic graphic group d in year *t* of the patent application. The coefficient β_y^d is a vector of time-varying estimates of inventions in year *y* 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 married mothers, 227 other married women (without children), 24,777 married fathers, and 4,711 other married men.

FIGURE 4 – SPEED OF PROMOTION TO TENURE



Notes: This figure plots the share of scientists in demographic group *d* who are promoted to the rank of associate or full professor within *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 5 – EVENT STUDY OF PROMOTION TO TENURE AFTER MARRIAGE

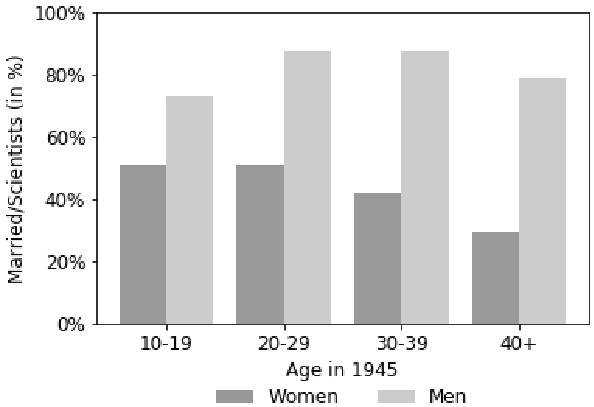
Notes: OLS estimates of β_y^d for demographic *d* (mothers, fathers, other married women, and other married men) in the regression:

$$y_{iy}^d = \beta_y^d EventTime_i + \delta_t + \alpha_a + \mu_f + \epsilon_{it}$$

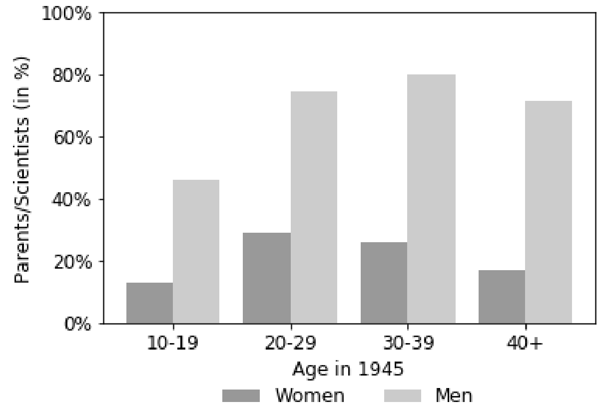
where y_{iy}^d indicates whether scientist i of demographic *d* was promoted to tenure in year *y* relative to marriage. The coefficient β_y^d is a vector of time-varying estimates for the probability of promotion to tenure in year *y* after marriage for a scientist of demographic *d* relative to probability of promotion to tenure in the year before marriage. 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 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 6 – SELECTION INTO MARRIAGE AND PARENTING:

PANEL A: SHARE OF MARRIED SCIENTISTS

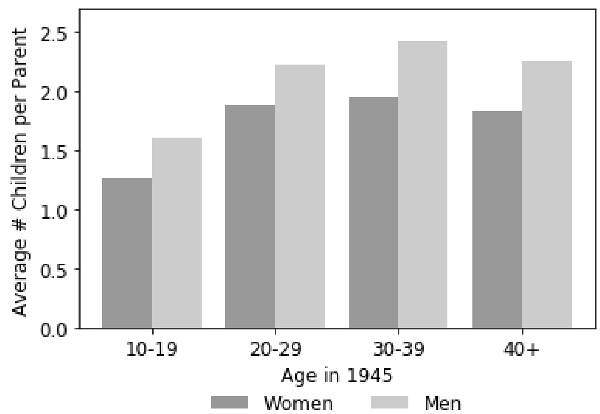


PANEL B: SHARE OF PARENTS



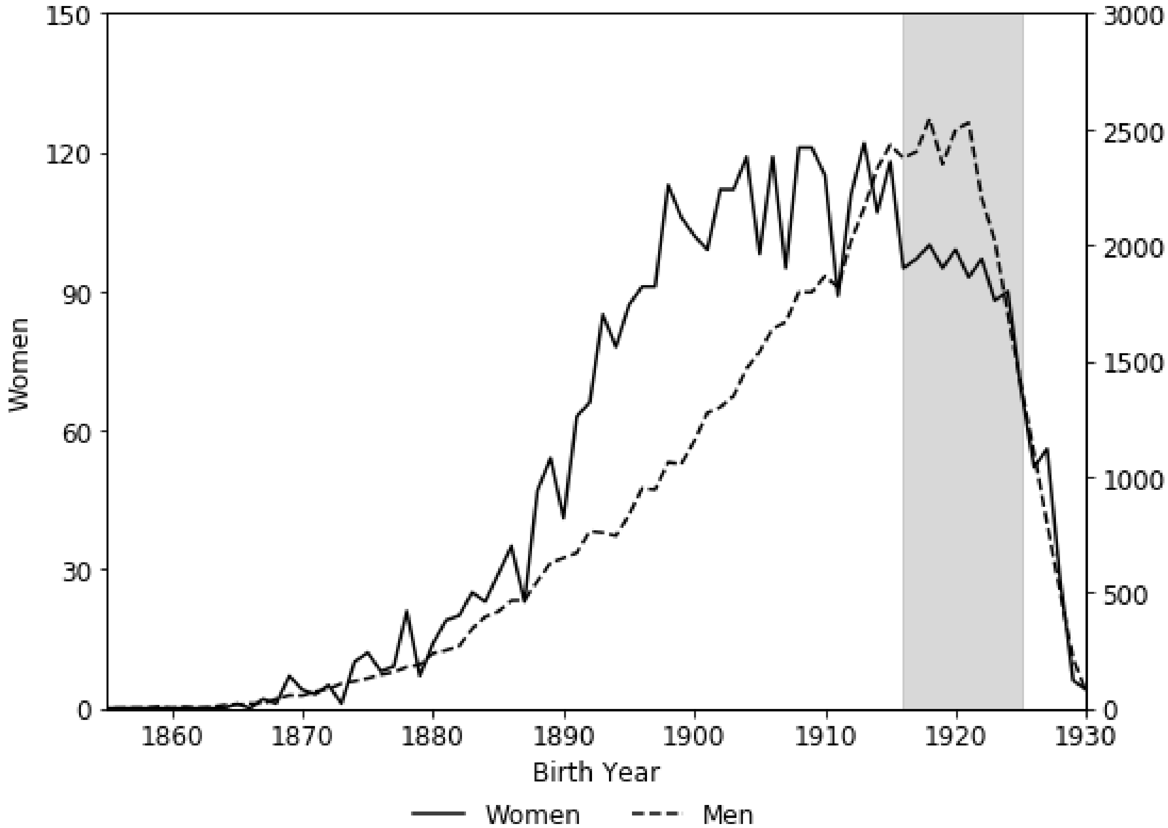
PANEL C: NUMBER OF CHILDREN PER SCIENTIST

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



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

APPENDIX A: 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 $1910 \le b_i + \mathrm{a} \le 1970$ 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

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

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

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

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.

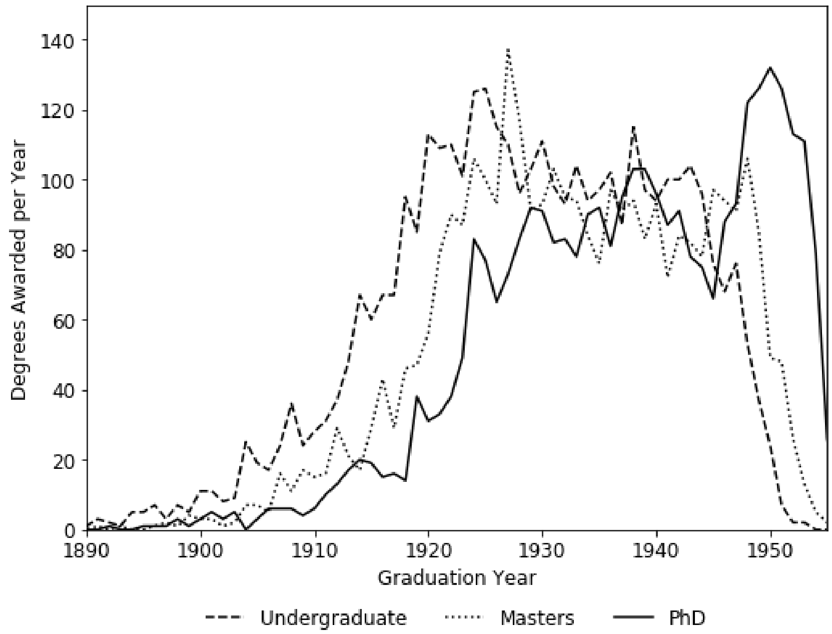
TABLE A2 – EFFECTS OF HAVING MORE CHILDREN ON THE PRODUCTIVITY OF MALE AND FEMALE SCIENTISTS

	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	Physical sciences	Physical sciences	Physical sciences	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

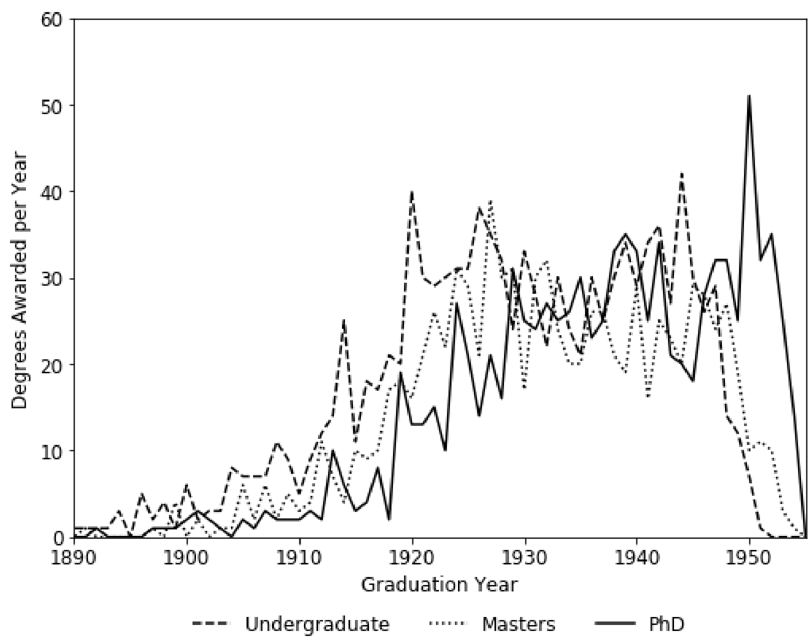
Notes: OLS estimates compare changes in the number of US patents by US scientists in the physical sciences per year throughout 1930–1970. Column (1) estimates $y_{it} = \beta_1 Parent_i + \beta_2 x\ Child_i + \beta_3 Female * x\ Child_i + \delta_t + \pi_b + \mu_f + \epsilon_{it}$, where the dependent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



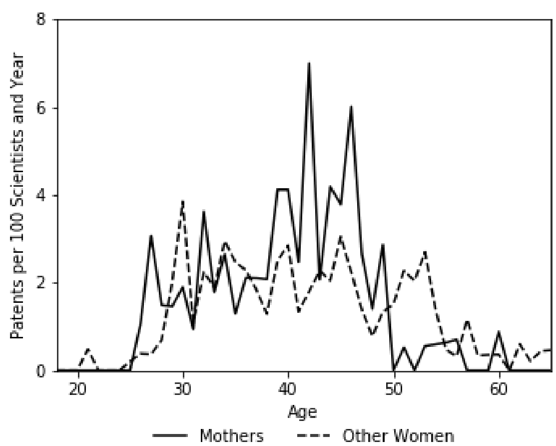
Notes: Degrees awarded per year to women who were active in American science in 1956. Panel A shows degrees for 4,032 female scientists in all disciplines (including the physical, biological, and social sciences, with a total of 3,755 undergraduate degrees, 3,265 master's, and 3,254 PhDs. Panel B plots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

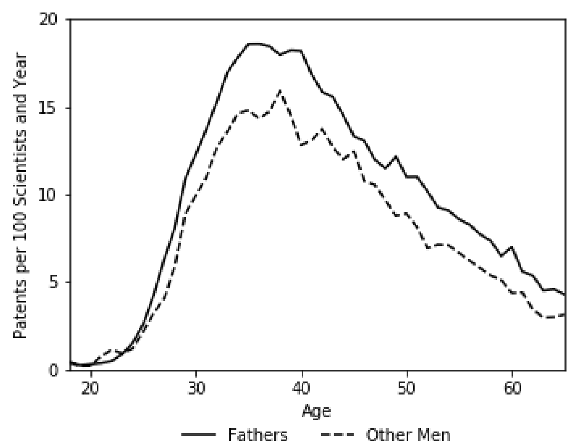
PANEL A: MOTHERS VS FATHERS

PANEL B: MEN VS WOMEN W/O CHILDREN

PANEL C: MOTHERS VS OTHER WOMEN

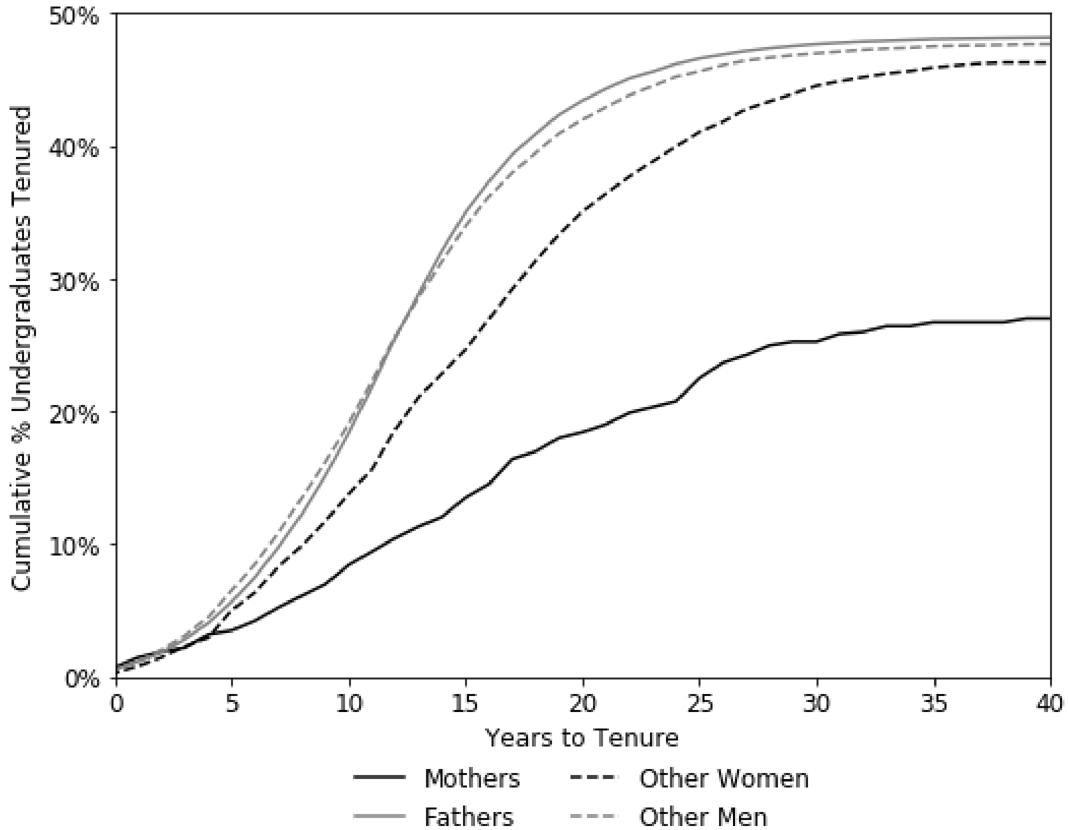


PANEL D: FATHERS VS OTHER MEN



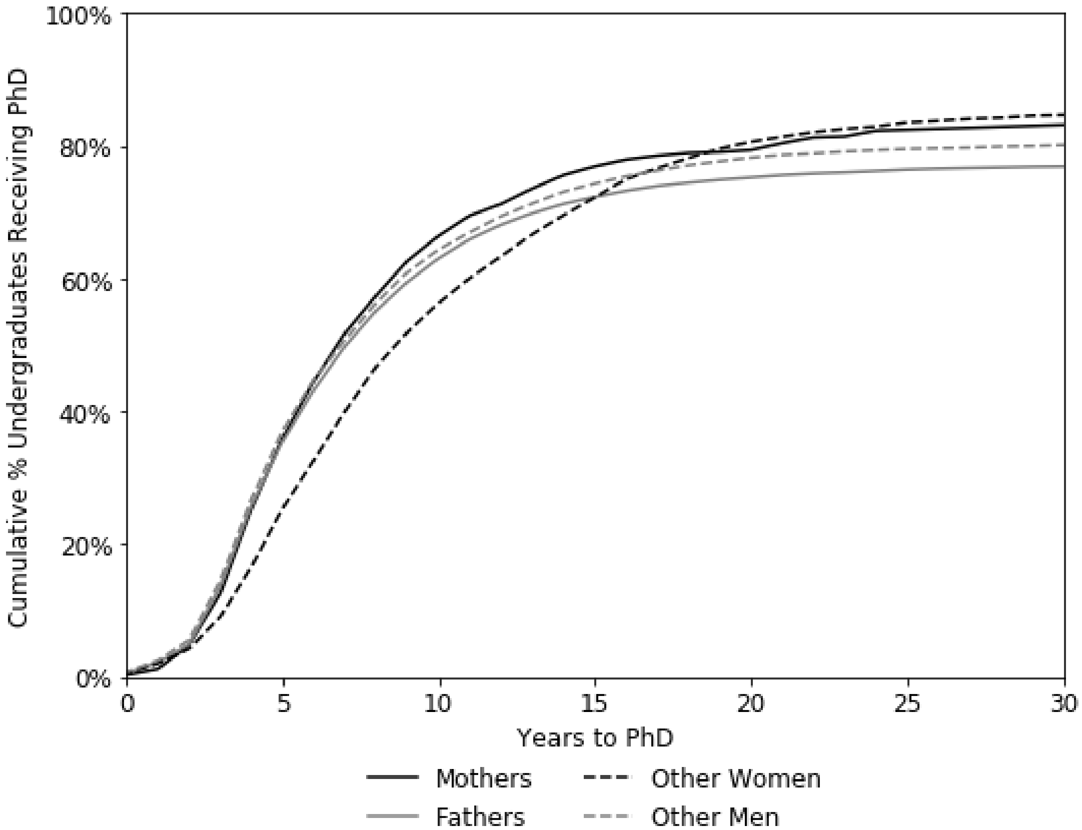
Notes: Panel A: 97,608 patents by 26,081 American scientists in the physical sciences, including 252 women and 25,829 men, who were active in US science in 1956 and had at least one child. *Panel B:* 23,713 patents by 9,287 American scientists in the physical sciences, including 920 women and 8,367 men, 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 – SPEED OF PROMOTION TO TENURE, COUNTING FROM UNDERGRADUATE DEGREE



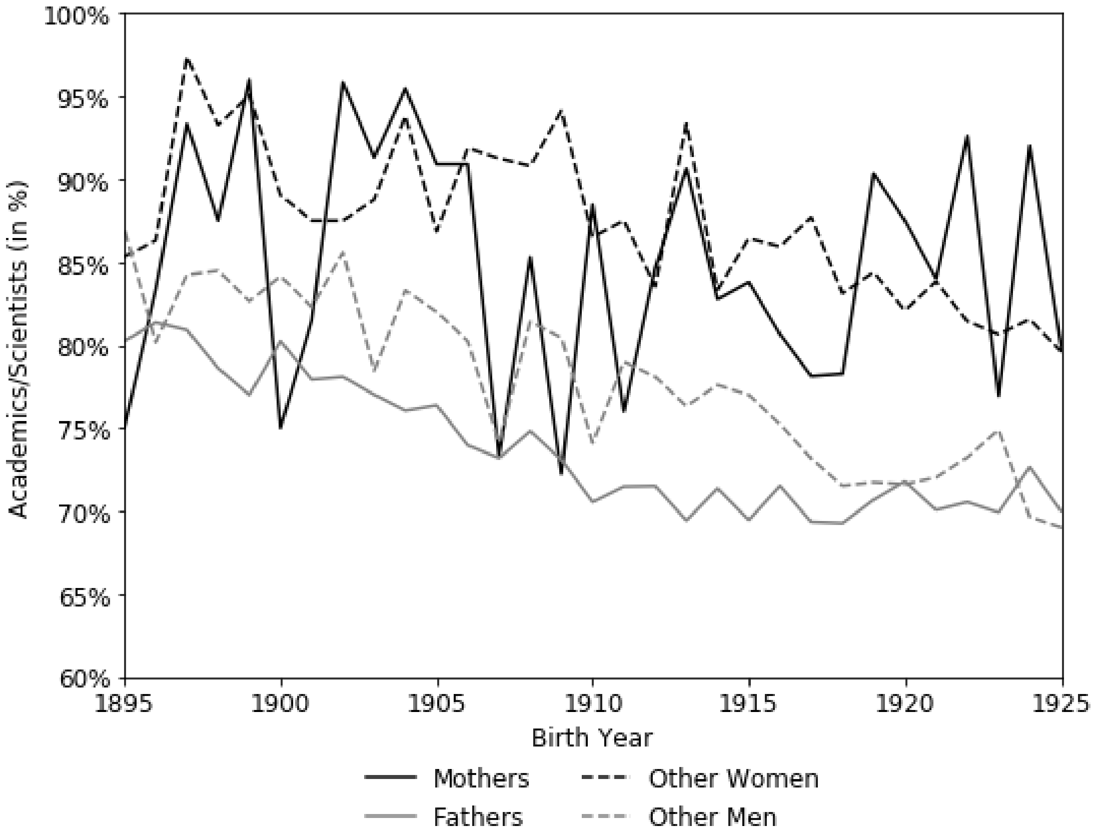
Notes: Years it takes to become a tenured professor (associate or full), counting from the year of receiving an undergraduate degree. Data include 689 mothers, 2,616 other women, 33,276 fathers, and 12,070 other men who received undergraduate degrees and were academics, of which 186 mothers, 1,216 other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

FIGURE A4 – SPEED TO PHD, COUNTING FROM UNDERGRADUATE DEGREE



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.

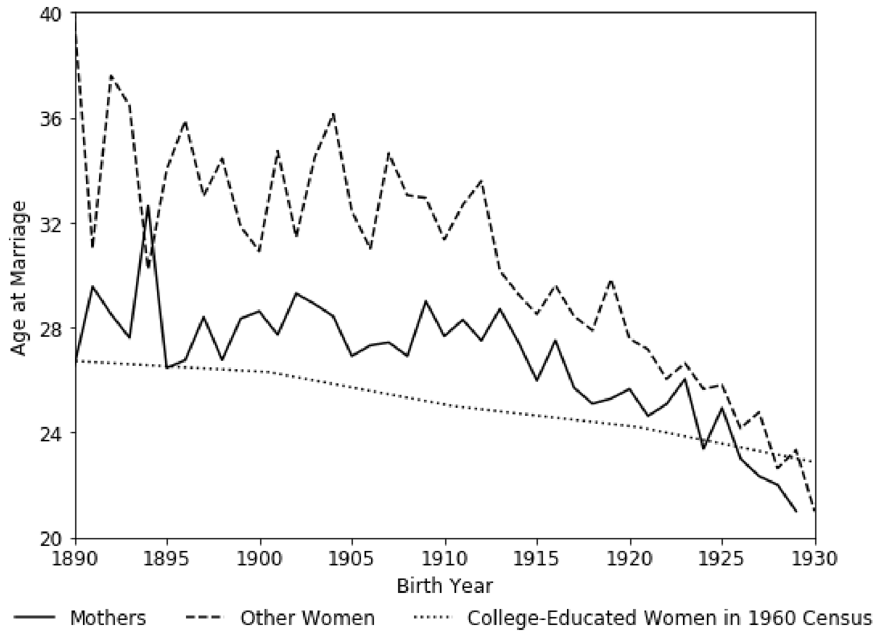
FIGURE A5 – PARTICIPATION IN ACADEMIA BY GENDER AND BIRTH YEAR



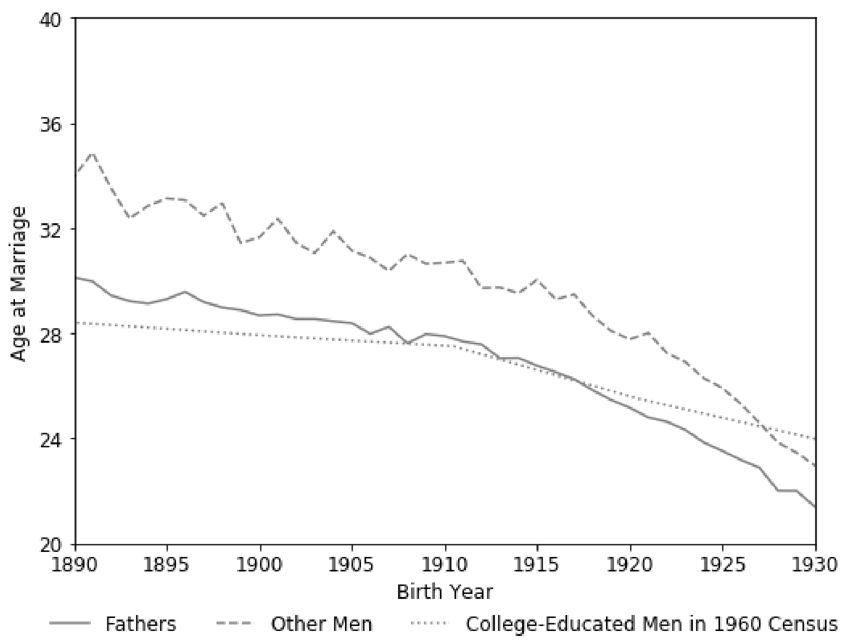
Notes: The share of scientists working in academia (measured by employment titles, including instructors, lecturers, professors) among all scientists. Data include 754 mothers, 2,783 other women, 36,140 fathers, and 13,269 other men who participated in academia and born between 1850 and 1940.

FIGURE A6 – MEAN AGE AT MARRIAGE BY BIRTH YEAR

PANEL A: WOMEN

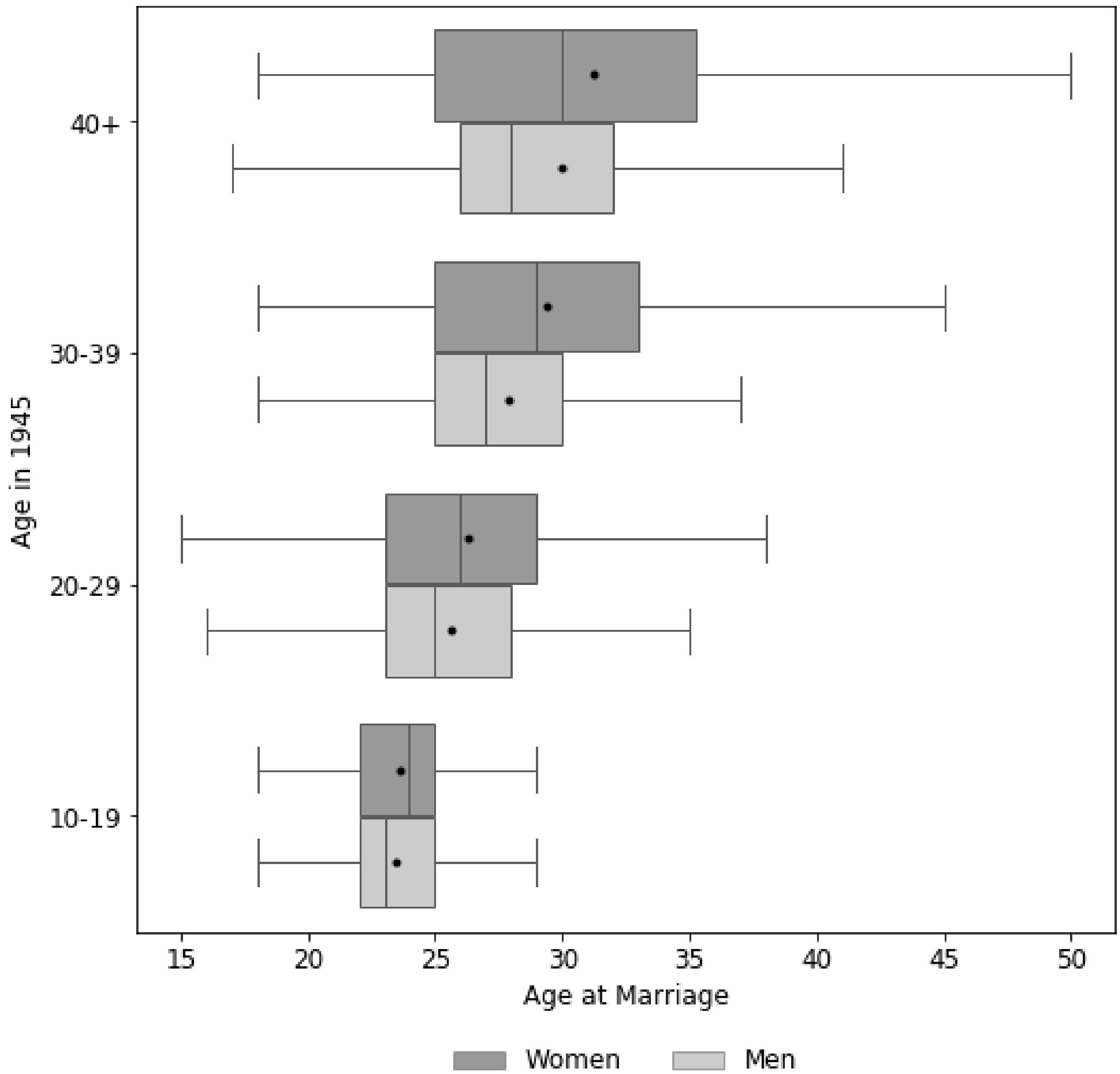


PANEL B: MEN



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.

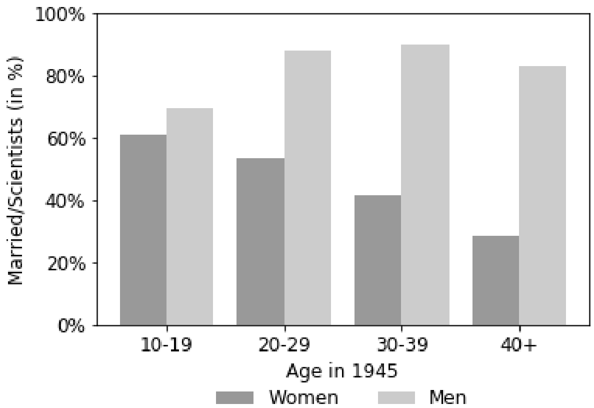
FIGURE A7 – AGE AT MARRIAGE BY BIRTH COHORT AND GENDER



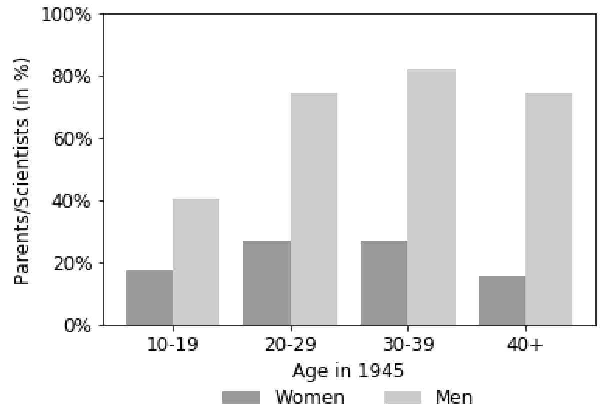
Notes: Mean and median ages at marriage for scientists across gender and birth cohorts. Birth cohorts are defined using the scientists' ages in 1945. We calculated each scientists age at marriage by subtracting their birth year from the year of their marriage. Both of these variables are reported in 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 A8 – 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

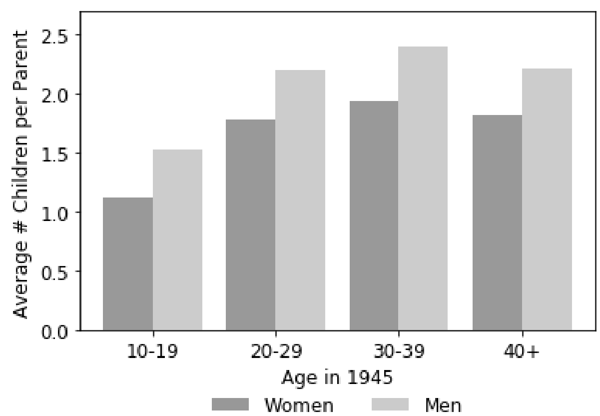


PANEL B: SHARE OF PARENTS



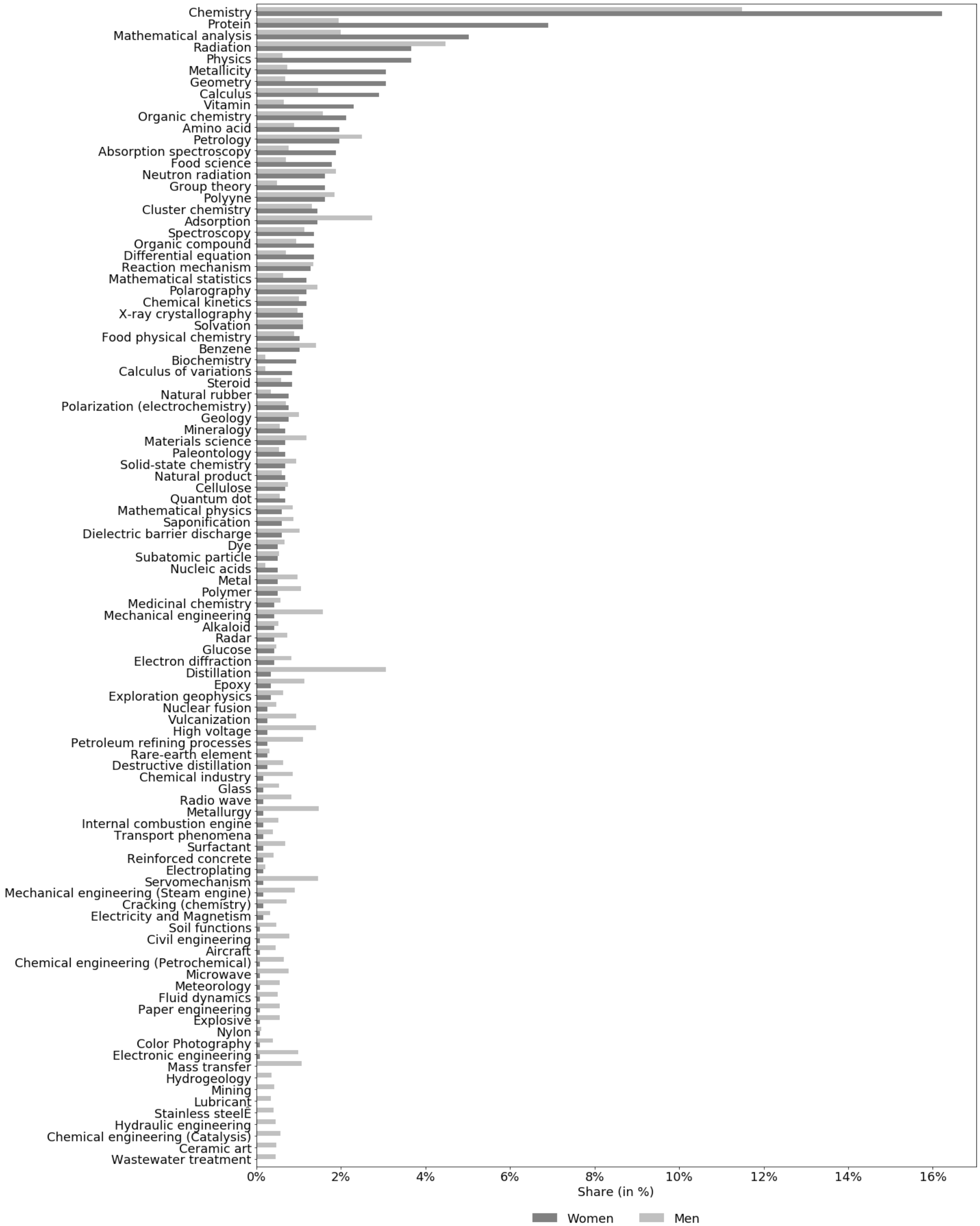
PANEL C: NUMBER OF CHILDREN PER SCIENTIST

PANEL D: NUMBER OF CHILDREN PER PARENT



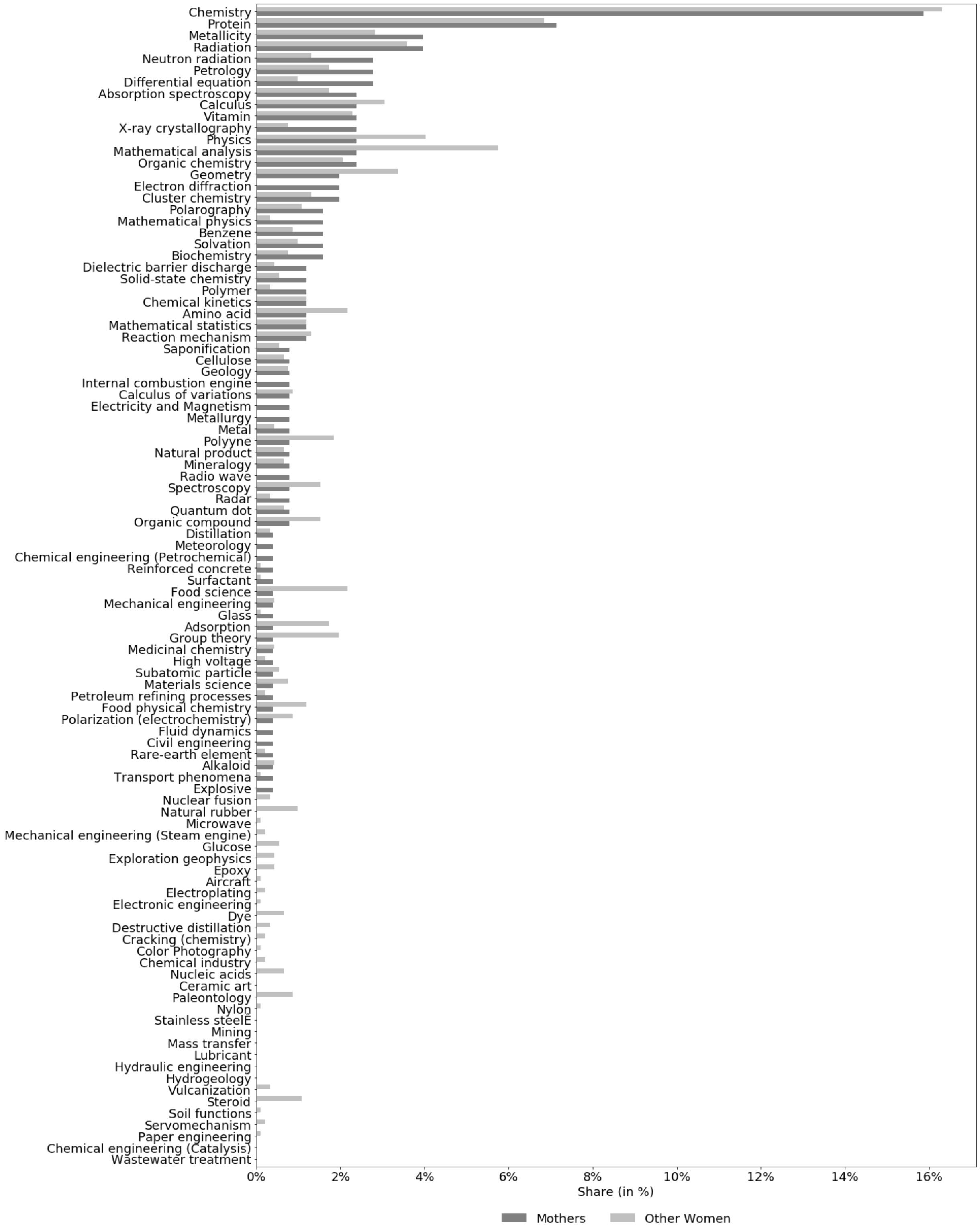
Notes: To investigate selection into marriage and parenting, we examine changes in the share of scientists who decided to marry and have children across birth cohorts, measured by their age in 1945, at the beginning of the baby boom (1946-1964). *Panel A* plots the share of scientists who were married. *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 A9 – 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 A10 – DISTRIBUTION OF SCIENTISTS ACROSS FIELDS: MOTHERS VS OTHER WOMEN

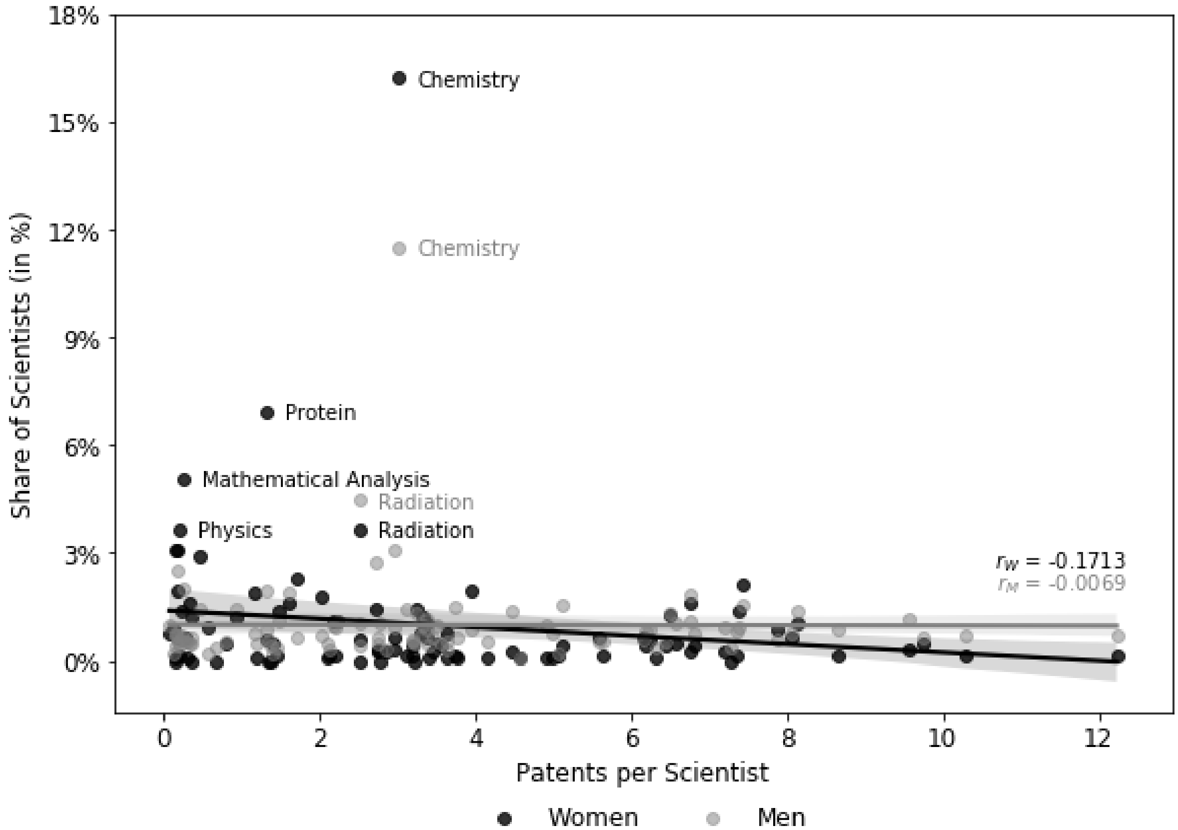


Notes: Share of female scientists across 100 fields, plotted separately for mothers and other women. Each scientist is assigned to a unique field, applying k-means clustering to information on their discipline and research fields (implementing an approach from Moser and San 2020).

FIGURE A11 – 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).

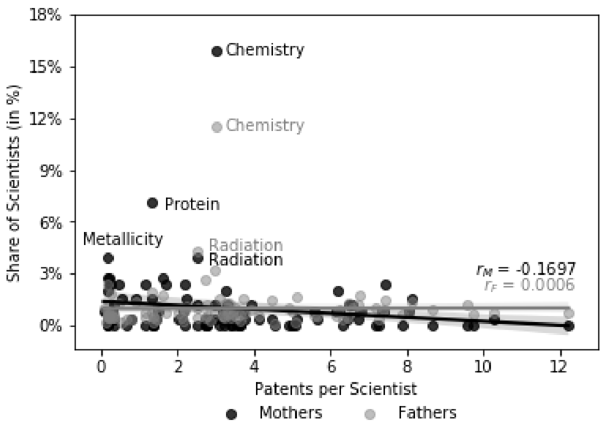
FIGURE A12 – FIELD DISTRIBUTION BY PRODUCTIVITY AND GENDER



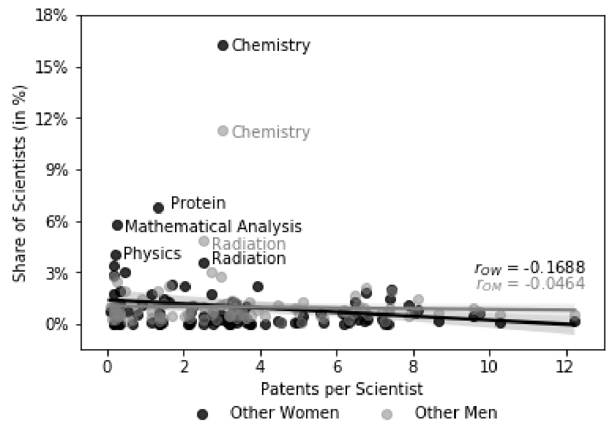
Notes: Share of scientists across 100 fields, plotted by patents per scientists per field and separately for women and men. Each scientist is assigned to a unique field, applying k-means clustering to information on their discipline and research fields (implementing an approach from Moser and San 2020).

FIGURE A13 – SELECTION INTO FIELDS: SHARE OF SCIENTISTS VS PATENTS PER SCIENTIST

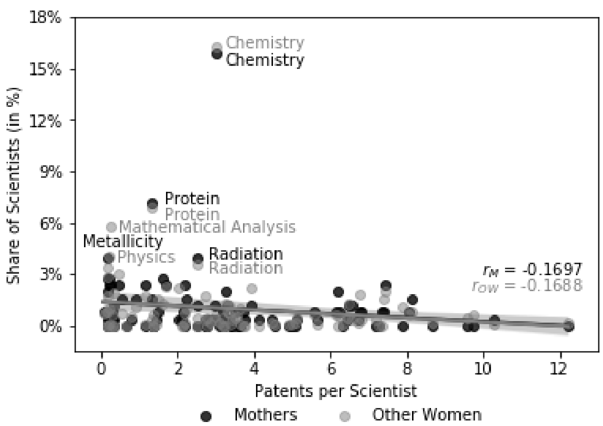
PANEL A: MOTHERS VS FATHERS



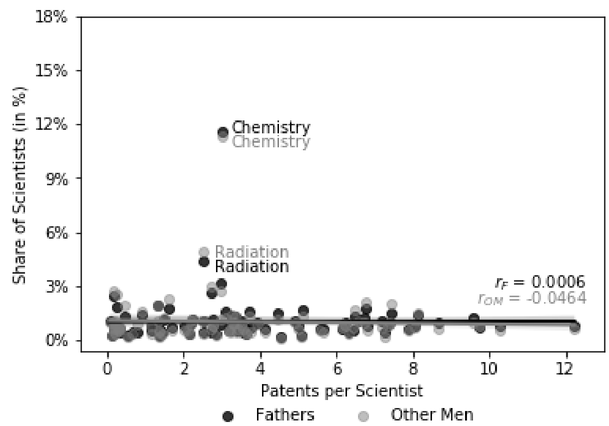
PANEL B: MEN VS WOMEN W/O CHILDREN



PANEL C: MOTHERS VS OTHER WOMEN



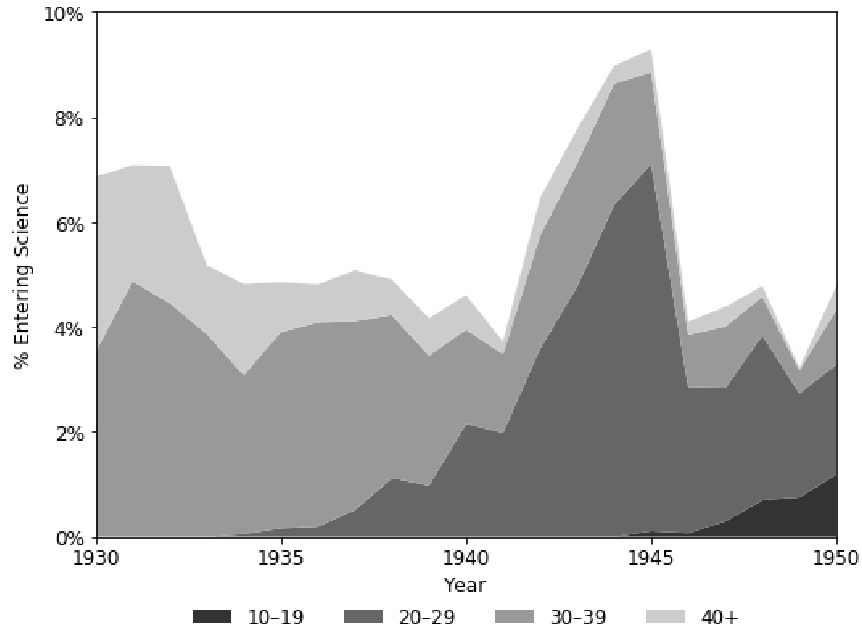
PANEL D: FATHERS VS OTHER MEN



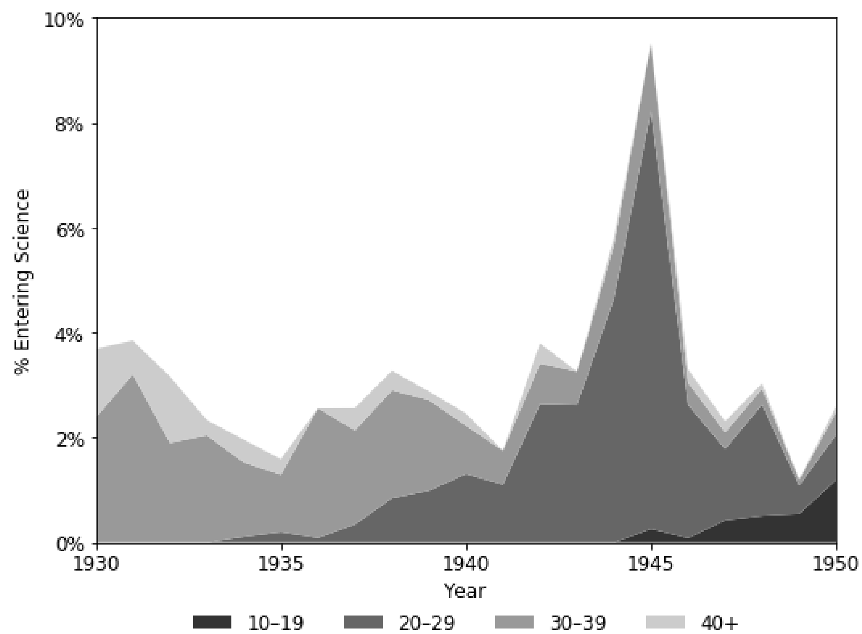
Notes: Panel A: Share of scientists across 100 fields, plotted by patents per scientists per field and separately for mothers and fathers. *Panel B:* Share of scientists across 100 fields, plotted by patents per scientists per field and separately for women and men who were not parents. *Panel C:* Share 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 A14 – 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).