ROSIE THE RESEARCHER
HOW FEMALE WWII HIRES CHANGED SCIENCE IN US FIRMS

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What are the productivity effects of hiring underrepresented talent? We investigate this question in the context of World War II, when a shortage of men forced US firms to hire female scientists. Using new data on the scientific personnel of US firms, we exploit firm-level variation in exposure to enlistment as an instrument for female hires. We find that firms exposed to enlistment hired 1.4 times more female scientists during the war. Firms that hired at least 1 female scientist during the war produced 1 additional publication per 11 scientists on average after the war - but no additional patents. Investigating mechanisms, we show that female hires were positively selected, introduced more novel research topics than men, and created positive spillovers for male incumbents. Data on job titles, however, reveal a misallocation of female talent within firms, diminishing productivity gains.

KEYWORDS: SCIENCE, INNOVATION, WORLD WAR II, GENDER

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Women continue to be underrepresented in science and other high-skilled occupations, especially among executives. According to the National Science Foundation (National Science Foundation 2023), just 34% of the US STEM workforce are women. In healthcare, 70% of the global workforce are female, but only 25% of workers in senior roles (World Health Organization 2019). This underrepresentation may have important productivity effects. At the level of the macroeconomy, decompositions of economic growth, have shown that the increased participation of Black and female workers in high skilled professions accounts for 20-40% of US productivity growth (Hsieh, Hurst, Jones, and Klenow 2019). At the firm level, entry barriers based on discriminatory preferences may lead firms to forego important gains in productivity (Becker 1957; Charles and Guryan 2008). Despite these important implications, there is little evidence to date on the causal effects of hiring women on firm productivity.

This paper uses exogenous variation in hiring due to WWII to investigate how an increase in exposure to female scientists changed the research productivity of US firms. To implement this analysis, we exploit a comprehensive census of scientists, the *American Men of Science* (MoS 1956), linked with their patents and publications. A key advantage of the MoS is that it allows us to observe scientists *within* firms, which is impossible with other sources. 13,920 scientists in the MoS (1956) worked for a total of 857 US firms. To measure exposure to enlistment, we link scientists with archival enlistment records for more than 8 million soldiers in the *U.S. World War II Army Enlistment Records, 1938-1946*. This linkage shows that 41% of firms employed at least one enlisted scientist. In the average firm, 10.7% of male scientists enlisted.

Importantly, enlistment is not correlated with the share of women among a firm's scientific staff or with the firm's research productivity before WWII. Scientists in firms exposed to enlistment produce similar amounts of patents and publications to scientists in other firms. Moreover, a scientist' research discipline cannot predict enlistment conditional on draft eligibility.

Difference-in-differences estimates show that exposure to enlistment forced firms to hire female scientists. Compared with other US firms, firms that employed enlisted scientists hired 139% more female scientists after 1939, the final year before the start of the WWII draft. This shift towards hiring female scientists was concentrated in the first few years of US involvement in WWII: firms exposed to enlistment hired 192% more women in 1942, 314% more in 1943 and 259% more in 1944.

Exposure to female hires increased the research productivity of hiring firms, measured by their scientists' publications. Firms that hired women during WWII produced 1 additional publication per 11 scientists and year after the war compared with other firms, a 45.4% increase relative to 1939. These results suggest that female

scientists had positive spillovers on their coworkers. Yet, their entry may have had negative effects on coworkers if female entrants competed with existing workers for the most attractive projects and resources. Analysis with a restricted sample of incumbent scientists, however, indicate a 35.3% increase in their productivity which suggests that positive spillovers outweighed potentially negative competition effects. Event studies show that most of these productivity gains occurred in the late 1940s and early 1950s, after the end of the war. Repeating these analyses for patenting, we find no significant increase in the average firm that hired female scientists.

Firms that hire women may be systematically different from other firms. For instance, they may value research more than personal traits. To investigate the influence of selection, we estimate instrumental variables (IV) regressions using exposure to enlistment as an instrument for female hires. IV estimates show that firms that hired women due to enlistment produced 0.42 more publications per scientist per year, an increase of 174% relative to 1939. This productivity increase is more than 4 times larger than the corresponding OLS estimate, suggesting that OLS estimates are downward biased. As with OLS, IV estimates for patenting are not statistically significant for the average firm.

Results are robust to including firm fixed effects, as well as variation in the size and the age composition of scientific staff. Excluding scientists who volunteered for military service leaves the estimates substantially unchanged. Estimates that exploit the staggered exposure of firms to enlistment confirm the main results (implementing Sun and Abraham (2021) and Wooldridge (2025)).

Within-firm estimates confirm that exposure to female scientists increases productivity. For these analysis, we compare research teams – groups of scientists in the same discipline and the same firm – within the largest employers of female scientists: DuPont, General Electric (GE), Shell, and American Cyanamid (including its pharmaceutical division Lederle Labs). Pooled IV estimates confirm that female hires increased publications per scientists but did not have a significant effect on patents. Separate IV estimates for the four firms, however, reveal important differences in the effects of hiring women across firms. While research teams that hired women at American Cyanamid became more productive in terms of both publications and patents, research teams at Shell produced more publications but not more patents. Female hires had no effect on the publication output of research teams at DuPont and GE.

Why do scientists become more productive in firms that hire women? First, we document that female scientists are positively selected. Female scientists are more likely to have a PhD or have attended an elite (Ivy Plus) university. Working with these high-ability women may raise the productivity of scientists in the same firm through

peer effects and knowledge spillovers. Second, we show that the research of female hires was more novel than the research of male hires. Using the text that describes scientists' research, we measure the similarity between the research of new hires and the research of incumbent scientists at the same firm. At every quantile of the distribution, female hires introduce more novel research than male hires. To investigate knowledge spillovers as a potential channel we examine co-authoring. Difference-in-differences estimates reveal that the increase in publishing is due to male scientists who publish 49.2% more after 1939 in firms that hired female scientists. This increase is driven by publications with male coauthors.

Analyzing unique data on job titles of scientists in the MoS, we show that, even though firms hired female scientists during WWII, many women were pushed into sex-types roles as research librarians or assistants, while few firms hired women as engineers or executives. Women accounted for 68% of research librarians, but only 0.7% of executives. Notably, only firms that placed women in executive roles – such as American Cyanamid – experienced an increase in patenting. Investigating promotions, we find that female scientists are 36.9% less likely to be promoted to leadership roles, conditional on experience and productivity. We also document that patents, but not publications, are associated with promotions.

These findings contribute to research on the effects of increasing female representation in organizations. Analyzing a 'zipper'-quota for Swedish politicians, Besley, Folke, Persson, and Rickne (2017) document an increase in the average competence of male politicians in response to the quota. Schaede and Mankki (2024) show that a primary school teacher quota in Finland raised average teaching talent. In response to a gender quota on the boards of public limited liability corporations in Norway, both the qualifications and compensation of female board members increased, without, however, any clear impacts on other parts of the firm (Bertrand, Black, Jensen, and Lleras-Muney 2019). In an experimental setting, González and Martınez-Marquina (2025) show that hiring quotas can be met with backlash if female hires underperform relative to males. Studying the gender composition of training units in Norway's army, Dahl, Kotsadam, and Rooth (2021) find that working with women temporarily causes men to have more egalitarian attitudes, without any persistent effects. To these findings we contribute evidence on the causal effects of hiring women on firm-level productivity.

Existing empirical analyses have shown that distortions in occupational choice raise the talent threshold for women. Studying variations in the gender composition of local talent pools for multinationals, Ashraf, Bandiera, Minni, and Quintas-Martínez (2024) find that female hires perform better when they are underrepresented in the candidate pool. Using variation in early life exposure to entrepreneurship in Denmark,

Mertz, Ronchi, and Salvestrini (2024) show that female entrepreneurs create more successful firms. Studying the entry of female scientists into patent-intensive research fields in STEM during WWII, Lubczyk and Moser (2025) find that female scientists produce better patents and publications. Focusing on college students, Lepage, Li, and Zafar (2025) show that women enrolled in STEM are positively selected and achieve better grades. We add to this literature by documenting distortions within firms, as highly-qualified women are placed into sex-typed roles.

Finally, we contribute to analyses of the long-run effects of WWII on female participation. Combining census data with retrospective surveys on married women's labor force participation between 1940 and 1950, Goldin (1991) shows that up to 54% of women who entered the labor force during the war had left again by 1950. Combining longitudinal surveys, Fujita, Ramey, and Roded (2024) show that female labor force participation remained elevated by 3p.p. after the war though women of childbearing age were "pulled" back into home production. To identify the causal effects of the war on female labor force participation, existing research has used geographical variation in enlistment rates across states Acemoglu, Autor, and Lyle (2004) show that states with a 10% higher mobilization rate experienced a 9.8% increase in women's labor force participation between 1940 and 1950. Fernández, Fogli, and Olivetti (2004) show that US states with a 10% higher mobilization rate experienced a 29% increase in female labor force participation for individuals whose mothers worked during the war. Studying the labor force participation of married white women in 1950 and 1960, Goldin and Olivetti (2013) show that the persistent effects of WWII on labor force participation were driven by married women with 12 or more years of schooling and without children. Jaworski (2014) shows that, in states with median enlistment rates, women obtained 0.16 fewer years of schooling, reducing their competitiveness after the war. Decomposing industry survey data from Pennsylvania, Shatnawi and Fishback (2018) find that WWII increased employer's demand for female labor. Rose (2018) shows that wartime investments in production were a key driver of increased in female labor force participation during WWII but that most of these effects had faded by the 1950s. To this literature, we add empirical evidence on the lasting impact of female WWII hires on research and innovation in US firms.

1. DATA

Our main data cover the lives and careers of 70,039 male and female scientists in the American Men of Science (MoS 1956), linked with their employers, publications, patents, and enlistment records.

Biographies of American Scientists

To collect biographical data, we have digitized the text of all 82,094 unique biographies in the *American Men of Science* (MoS 1956). A comprehensive database of scientists, this dataset was originally collected by James McKeen Cattell, the first professor of psychology in the United States and the first editor of *Science* for nearly 50 years. In the MoS, Cattell created "for the first time a fairly complete survey of the scientific activity of a country in a given period" (Cattell 1906, p.v). With support from the Carnegie Institution, Cattell published his data "to make men of science acquainted with one another and with one another's work." He continued to update the MoS until his death; the 1956 edition was published by Cattell's son Jacques.

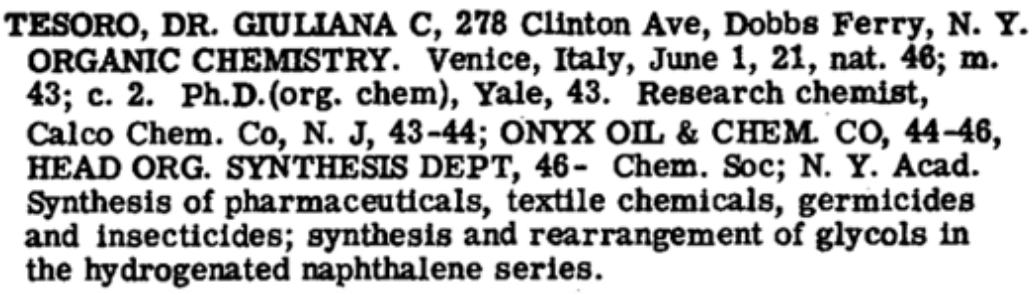
Entries are based on membership in scientific societies (such as the American Mathematical Society or the American Society of Bacteriologists) and subject to a comprehensive review from "scientific societies, universities and colleges, industrial laboratories and other institutions (Cattell 1956, p. iv). In the editor's preface, Cattell (1956) 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 advisory capacity."

To identify female scientists, we use historical gender frequencies of first names in the US Social Security Administration Records (SSA) between 1880 and 2011, implemented in Python's *gender-detector* package. This approach outperforms hand-matching in a benchmarking exercise that uses graduates of women's colleges as true positives (Kim and Moser 2025). The algorithm assigns the gender of 70,780 scientists (86.2%), including 4,220 women and 66,560 men. Data on marriages and children allow us to control for variation in the family status of male and female scientists. 81.7% of scientists are married, and 71.1% have at least one child. We use these data to identify women who are engaged in childcare if they have children and if they do not list a job after marriage.

Information on scientists' precise birth years allow us to investigate changes in productivity across the life cycle, and to control for age and cohort fixed effects. We also use birth years to create a high-quality match between scientists and their patents. Birth years are available for 81,461 scientists (99.2%); both birth years and gender are known for 70,230 scientists (85.5% of all scientists in the MoS 1956).

Data on the year when a scientist started their first job allows us to identify the year when they entered science. For example, Giuliana Tesoro started her first job as a research chemist at the Calco Chemical Company in New Jersey in 1943, when she

earned her PhD at Yale.



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.

Scientists in US Firms

Detailed data on the employment history of each scientist allow us to identify scientists employed at firms over time. First, we use rule-based text classification to assign employers to five categories: firms, universities, public sector jobs, school teaching, and being out of the labor force. Classification rules use key words, such as "company", "corporation", or "limited" to identify firms and "university", "college", "medical school", or "law school" to capture universities.[1] Next, we clean and harmonize names of firms that employed scientists. Specifically, we remove punctuation, expand common abbreviations (e.g. "corp." to "corporation"), and harmonize different spellings of the same name. We then link the cleaned firm names in the MoS 1956 with firm data from the Center for Research in Security Prices (CRSP). We link 13,920 scientists to 857 "permanent company identifiers" (permco) in CRSP, which allow us to track firms over time, even if they change their names, or merge with another firm. 726 firms are direct matches; we link another 131 manually. For instance, Giuliana Tesoro's first employer, the Calco Chemical Company, was a manufacturer of synthetic dyestuffs (e.g. for camouflage uniforms). But when dye intermediaries became important inputs into sulfa drugs in the 1920s and 1930s, the American Cyanamid Company acquired Calco Chemical in 1929. The permco identifiers allow us to link and trace these changes.

Scientists are "out of the labor force" in a given year if they do not list an employer or job in that year. Using information on each scientists' year of marriage, their children, and their degrees we distinguish time spent outside the labor force into childcare, education, and other non-employment spells.

Job Titles

Detailed data on job titles allow us to observe the work that scientists performed within firms. Giuliana Tesoro worked as a "research chemist" for Caclo between 1943 and

[1] Rule-based classification assigns 80.7% of female scientists' employment spells between 1930 and 1955 to one of the five employer types. We manually classify all remaining employers that account for at least 20 employment years among scientists.

1946 before becoming the "head of the department for organic synthesis" at the Onyx Oil and Chemicals Company in 1946. 13,920 scientists hold 8,314 distinct jobs; 224 female scientists have 184 distinct jobs. The most common jobs for scientists of either gender are "research chemist" (15.4% of men and 17.6% of women) and "chemist" (4.2% of men and 5.9% of women).

Before WWII, most jobs are only done by men. Among 42 common jobs held by 50 or more scientists, just 7 employ a woman before 1940 (Figure 1). As more firms employ female scientists during WWII, women enter new roles. Between 1940 and 1955, 22 of the 42 most common jobs are held by at least one female scientist (Figure 2).

We group 184 jobs held by female scientists into leadership, research, assistant, librarian, and other roles. First, we create a dictionary of distinctive terms that identify a role. For instance, the job titles “supervisor”, “director”, and “chief” denote leadership roles, while “librarian”, “bibliograph” and “editor of engineering reports” indicate the role of a librarian. We use these dictionaries to classify all job titles held by male scientists. 90.6% of 8,226 job titles held by male scientists between 1935 and 1955 map to the dictionary of job titles held by women.[2]

In 1939, the last year before the United States entered WWII, the average firm with two or more scientists employed 35.1% of its scientists as researchers, 31.8% in leadership roles, 12.7% as assistants, 0.1% as librarians and 20.3% in other roles.

Assigning Scientists to Disciplines

To examine the influence of female scientists within firms, we use the keywords that describe each scientist’s research to assign scientists to 15 distinct disciplines. This matching exploits a unique feature of the MoS: Scientists ranked each other to identify the “leading men” within their discipline, and Cattell attached a star to the winners of this contest. Visher (1947) reports the names and disciplines of 2,605 stars elected between 1906 and 1939. Airoldi and Moser (2025) match these stars to MoS (1921) and use the linkage to train a nearest centroid matching algorithm, which then assigns remaining scientists to a unique discipline based on the text describing their research topics. We extend this process to the MoS (1956).

Methodologically, we use a GloVe model (pre-trained on 300-dimensional word vectors from Wikipedia 2014 and Gigaword 5, Pennington, Socher, and Manning (2014)) to create vector representations of scientists’ research subjects and topics. With this vectorization, a scientist is represented by the average of the GloVe vectors of

[2] Among the remaining 1,532 job titles, men are most likely to be “v. pres” (0.5%), “metallurgist” (0.4%), and “mem. staff" (0.4%).

the words that describe their research. We use the subject and research topics of the 7,611 scientists whom we can assign to a unique discipline to train the nearest centroid classifier model (using Euclidian distance as the distance metric) and apply the trained algorithm to assign remaining scientists uniquely to the disciplines.

A key advantage of GloVe embeddings and the nearest centroid metric is that they can recognize similar words that lie outside the average human's vocabulary but may be used by scientists. For example, the target words for "frog" include "toad," along with scientific terms such as "eleutherodactulus" and "leptodactylidae", which would be difficult to recognize in manual assessments. Giuliana Tesoro describes her research topics as "Synthesis of pharmaceuticals, textile chemicals, germicides and insecticides; synthesis and rearrangement of glycols in the hydrogenated naphthalene series." Based on this information, we assign her to the discipline "chemistry."

Measuring the Novelty of Scientists' Research Topics

We use the text that describes a scientist's research to capture the novelty she contributes to the firm. Specifically, we measure the similarity between the research topics of new hires and the stacked research topics of all incumbents scientists at the same firm.

To measure novelty, we calculate average word embeddings for research topics at the firm level. We use word embeddings because they capture words that are similar in meaning, as defined by each word's local context (Ash and Hansen 2023). For instance, word embeddings reveal that Giuliana Tesoro's research topic "textile chemicals" is similar to the keyword "dyestuffs," an important business segment for her employer American Cyanamid.[3] We use pre-trained vectors from fastText (Joulin, Grave, Bojanowski, and Mikolov 2016, pre-trained on Wikipedia texts) and calculate the firm's prewar knowledge frontier using the tokenized research topics and research discipline of the firm's incumbent scientists between 1935 and 1939. We compute word embeddings for scientists hired between 1940 and 1946.[4] The key advantage of using fastText is that it splits words into subwords, *n*-grams (with *n* between 3 and 6) with prefix and suffix annotation. Subword vectors are particularly good at capturing the similarity between compound terms that are common in research. For example, fastText recognizes that the word "chip" is closely related to the term "microcircuit" because it matches well with the subwords "micro" and "circuit."

[3]The terms "textile chemicals" and "dyestuffs" only share 2 of 15 unique letters, resulting in low string similarity if measured by Levenshtein distance (15 edits required to transform one term into the other) or Jaccard index (0.133 overlap). The terms, however, appear in very similar context which suggests that they are close substitutes *in meaning*. Word embeddings capture this similarity and assign a score of 0.742 on a scale from 0 to 1.

[4]We include research disciplines to avoid inflated similarity from comparisons between sparse vectors.

We define two measures of novelty: First, we use the average word embeddings across incumbents to calculate the average distance between a new hire and all incumbent scientists at the same firm. Second, we use the centroid of the firm embeddings matrix to compute the difference between a new hire and the average scientist at the firm. Formally, we measure novelty as $1 - \text{cosine similarity}$, defined on the unit interval.

Matching Scientists with Publications in Microsoft Academic Graph

To measure individual-level differences in research productivity, we match scientists with their publications in Microsoft Academic Graph (MAG, Sinha, Shen, Song, Ma, Eide, Hsu, and Wang 2015), using their first, last, and middle names. To minimize false positives, we focus on English-language publications and authors with at least one publication between 1900 and 1970. To measure research productivity at the firm level, we add all publications by the scientists that the firm employed in that year.

The average scientist produced 16.6 publications between 1900 and 1970. Albert Sabin, the inventor of the oral polio vaccine, has the largest number of publications, with 980 articles and books. The endocrinologist Miriam Elizabeth Simpson, who earned the first PhD in anatomy at the University of California, is the most published female scientist, with 249 publications. Giuliana Tesoro published 91 papers over her career.

DuPont and GE are the firms with the largest publication output, each producing more than 300 papers per year in the 1950s. The average scientist employed at DuPont publishes 0.29 papers per year between 1935 and 1955. The average scientist at GE publishes 0.40 papers per year. Scientists at Lederle/American Cyanamid, the company that acquired Giuliana Tesoro's first employer Calco Chemicals, on average produce 0.49 publications per year.

Matching Scientists with Patents

As an additional measure of research productivity, we count the number of successful patent applications by each scientist per year and aggregate these data at the firm-level. This approach exploits a matching process from Moser, Parsa, and San (2024) that links all 82,094 scientists in the MoS (1956) with their US patents between 1910 and 1970 from Google Patents, using scientists' full name, age, and discipline. To assess the match quality between scientists and patents, we use patents that are matched to scientists when they are 0-18 years old as a measure for false positive matches and choose matching rules that minimize the share of false positives.

Using her full name and her June 1921 birthdate, we link Giuliana Tesoro to 89 patents. The firm with the highest number of patents is DuPont, producing more

than 200 patents a year in the 1930s, followed by GE, Eastman Kodak, and Monsanto Chemical. Scientists on average produce 0.25 patents per year at DuPont and GE, 0.22 patents per year at Lederle/American Cyanamid, 0.35 at Monsanto, and 0.51 at Eastman Kodak.

Name-based matching may understate women's contributions to innovation if women change their names upon marriage. The MoS, however, reports the birth name of most married female scientists – sometimes along with the husband's name, as in the case of Julianne Prager. In the physical sciences, 93.1% of married female scientists (434 women) report their birth name – only 32 married women do not. More generally, we are unlikely to miss many patents: Just 38.8% of female scientists married (1,560 women), and just 466 married women worked in the physical sciences, where scientists are most likely to patent. We link Julianne Prager (née Heller) to 7 patents:

PRAGER, DR. JULIANNE H(ELLER), (MRS. STEPHEN PRAGER), 1230 Rose Vista Court, St. Paul 13, Minn. ORGANIC CHEMISTRY. Boston, Mass, June 5, 24; m. 48. Sc.B, Brown, 46; Ph.D.(org. chem), Cornell, 53. Research assoc. biochem, Utah, 51-52; SR. CHEMIST, MINN. MINING & MFG. CO, 52- Chem. Soc. Synthesis of macrocyclic ketones, C^{14}-labelled steroids and polymers.

Matching Scientists with WWII Enlistment Records

To measure variation in exposure to enlistment, we exploit a linkage between the MoS (1956) and enlistment records from the National Archives for 9,025,234 soldiers in the US Army and Air Force 1938-46 (Chen and Moser 2025). 10,285 scientists enlisted in WWII: 19% of 54,424 draft-eligible men between the ages of 18 and 44 between 1938 and 1946. 39% of male scientists born between 1918 and 1927 enlisted in the Army between 1941 and 1946. 41.4% of firms employ at least one scientist between 1930 and 1955 who enlists in WWII. In the average firm, 10.7% of scientific employees enlist.

We use Army serial numbers to distinguish scientists who were drafted from scientists who volunteered. A soldier's 8-digit serial number serves as their unique identifier in Army records. The first digit indicates enlistment status: volunteers' serial numbers start with a 1, draftees' start with a 3 or a 4, and members of the National Guard receive a number starting with 2.

57% of enlisted scientists were drafted and 39% volunteered.[5] The remaining 3.3% served in the National Guard. Volunteering peaked immediately after the attack on Pearl Harbor: 64% of all volunteers enlisted in 1942. After December 5, 1942, an executive

[5]Some volunteers may be draftees who took advantage of a rule that granted draftees who enlisted as volunteers before their induction some choice over their unit and terms of service (Fouka 2020).

order restricted voluntary enlistment to ensure government control over the labor force (Fouka 2020; Qian and Tabellini 2025).[6]

2. Enlistment as a Source of Exogenous Variation in Female Entry

Event Studies

To investigate the causal effects of female hires on the productivity of US firms we first test whether firms that were more exposed to WWII enlistments hired more female scientists after the start of the WWII draft. Specifically, we estimate OLS event studies that compare changes in female hires after 1939 across firms that were differentially exposed to enlistment:

$$\text{Female Entry}_{jt} = \alpha_j + \phi_t + \sum_{t, t \neq 1939}^{T} \left(\mathbb{1}[T = t] \times \text{Enlistment}_j \right) \beta_t + \varepsilon_{jt} \tag{1}$$

where *Female Entry*$_{jt}$ counts female scientists hired by firm j in year t. Firm fixed effects α_j control for variation in female entry across firms that is constant over time, for instance due to variation in the rigidity of working hours (Cortes and Pan 2016; Goldin and Katz 2016; Wasserman 2023). Year fixed effects ϕ_t account for variation in female entry over time, for instance, due to changes in female labor force participation. *Enlistment*$_j$ indicates firms that employ at least one enlisted male scientist. 41.4% of firms are exposed to enlistment in this way. 1939, the last full year before the October 1940 passage of the Selective Training and Service Act (Pub. L. 76-783, 54 Stat. 885) is the excluded period. Under the identifying assumption that, in absence of WWII, firms with enlisted male scientists would have continued to hire women at the same rate as other firms, β_t estimates the causal effect of having enlisted male scientists on female hires.

Before the war, changes in female hiring were comparable for firms with and without enlisted scientists; event study estimates are close to zero and not statistically significant (Figure 3). After 1940, however, firms with at least one enlisted male scientist, hired 12% more female scientists in 1941 (p=0.300), 192% more in 1942 (p = 0.020), 314% more in 1943 (p = 0.002), 259% more in 1944 (p = 0.014), and just 46% more in 1945 (p = 0.156). After the war, event study estimates indicate no significant difference in hiring women across firms with and without enlisted male scientists for years between

[6] In December 1942, President Roosevelt issued Executive Order 9279 which prohibited voluntary enlistments for men aged 18-38 unless they had submitted an application for enlistment before the order's effective date. While some scholars argue that the Army remained open to volunteers after 1942 (see e.g. footnote 9 in Rose 2018), enlistment records indicate that voluntary enlistments no longer constituted a major source of manpower after order 9279 had been issued.

1947 and 1955.

This transitory increase in female hires at US firms during WWII confirms that firms considered women "temporary employees, 'keeping the seat warm' for men" (Rossiter 1995, p.1). Moreover, our results are consistent with prior empirical research on female labor force participation (e.g., Goldin 1991; Rose 2018; Fujita et al. 2024). Comparing census data with retrospective surveys on married women's labor force participation between 1940 and 1950, Goldin (1988) shows that up to 54% of women who entered the labor force during WWII had left again by 1950. Analyzing the spatial distribution of female employment in war-related industries, Rose (2018) shows that, even though wartime investments in production encouraged female labor force participation, most of these effects had faded by the 1950s.

Effects of Enlistment on Female Hires

As more men enlisted in the war, US firms hired more female scientists (Figure 4). In 1942-44, four times as many female scientists entered US firms relative to 1939. By comparison, the increase in male hires was much smaller, at 1.9 times the 1939 level. In absolute terms, the number of female scientists in US firms more than doubles from 36 in 1939 to 85 in 1943 and to a high of 93 in 1944 (Figure 5). After the war, the number of female scientists remains roughly constant, between 87 in 1948, 85 in 1951, and 89 in 1955, while the number of male scientists continues to increase. As a result, the share of female scientists peaks during the war, at 1.7% in 1944, up from 1.0% in 1939. By 1955, the share of female scientists has fallen back to 1.1% (Figure 6).

To identify the average treatment effect of enlistment on female hires at the treated firms we estimate difference-in-differences OLS regressions:

$$\text{Female Entry}_{jt} = \alpha_j + \phi_t + \left(\mathbb{1}[t > 1939] \times \text{Enlistment}_j\right)\gamma + \varepsilon_{jt} \tag{2}$$

Female Entry$_{jt}$ counts female scientists hired by firm j in year t. Firm fixed effects α_j control for variation in female entry across firms that is constant over time. Year fixed effects ϕ_t account for variation in female entry over time. The treatment variable *Enlistment*$_j$ is an indicator variable for firms in which at least one male scientist enlists in the war. Under the assumption that, in the absence of the war, female hiring would have evolved similarly in firms with and without enlisted scientists, γ identifies the effect of exposure to enlistment on the representation of women in US firms.

OLS estimates indicate that the enlistment of male scientists created a large increase in US firms' hiring of female scientists: firms with enlisted male scientists hire 139% more women after 1939 compared with other firms (Table 3, column 1). Alternative

specifications measure exposure to enlistment by the share of male scientists in firm j who enlist during the war. Firms that experience a 1 standard deviation increase in enlistment exposure hire 27.9% more female scientists during the war (Table 3, column 3). By 1946, 55% of female WWII hires have left their wartime employers, compared with 43% of male hires (Figure 7). By 1955, 4 of 5 female wartime entrants have left their wartime employers.

The increase in female hires is robust to excluding volunteers.[7] Restricting treated firms to those with at least one drafted scientist, OLS estimates of Equation 2 show that firms with drafted male scientist hire 137% more women after 1939 compared with other firms (Table 4, Column 2).

Estimates with staggered treatment – exploiting variation in exposure to enlistment over time – confirm the increase in female hires. Specifically, we define an indicator variable for years after a scientist employed by firm j enlists in WWII. We include scientists who enlist in year t and worked for the firm in years t, $t-1$ and $t-2$. Most firms are first exposed to enlistment in 1941 (29.2%), 1942 (39.6%), or 1943 (15.6%, Figure 8). Excluding voluntary enlistment and focusing on draft exposure, 86% of exposed firms have lost at least one male scientist to enlistment by 1943 (Figure 9).

Assuming homogeneous treatment effects over time, two-way fixed effects imply that exposed firms hire 201% more female scientists each year after exposure to enlistment (Table 5, Column 1). Equivalent estimates for draft exposure indicate an 196% increase in female hires (Table 5, Column 2).

Allowing for treatment effect heterogeneity over time, we estimate the effects of staggered exposure using the extended two-way fixed effects estimator (ETWFE, Wooldridge 2025).[8] ETWFE estimates, which compare exposed firms to never-treated firms, show that firms exposed to enlistment hire 209% more female scientists after exposure. Firms exposed to the draft hire 206% more female scientists (Table 5). ETWFE event study estimates confirm that firms exposed to enlistment hire more female scientists. The estimated effect is largest in the third year after exposure when exposed firms hire 5.3 times more female scientists than in 1939. Exposed firms continue to hire more female scientists 5 years after exposure (Figure 10).

Comparing ETWFE event study estimates with alternative estimates using the Sun and Abraham (2021) estimator (Figure 10) suggests that the inclusion of leads of the treatment variable biases coefficients for lagged treatment variable downwards.

[7] Caprettini and Voth (2023) show that there was substantial variation in volunteering across the US, partly driven by past government spending.

[8] With absorbing treatment and no additional covariates beyond time and unit fixed effects, the saturated Wooldridge (2025) ETWFE estimator is equivalent to the Sun and Abraham (2021) and Callaway and Sant'Anna (2021) estimators.

Therefore, the ETWFE estimator omits the pre-period coefficients. Identification relies on the assumption of parallel trends starting in $t-1$. Including redundant and collinear regressors creates attenuation bias; this bias may be reduced by averaging the level difference between treatment and control over the pre-treatment period (Wooldridge 2024).

Pre- and Post-WWII Employment of Female WWII Hires

The enlistment of male scientists forced US firms to hire female scientists. Where did these women come from? And where did they go after the war? To answer these questions, we examine the employment trajectories of female WWII hires before and after the war. In total, WWII drew in 113 women into employment as scientists at US firms. 30.0% of women were employed by universities or colleges, 20.8% of female WWII hires transitioned from prewar employment at another firm, 8.3% worked in the public sector, and another 1.7% were schoolteachers. 30.8% of female WWII entrants were outside the labor force before their war-time employment. Most of these women (20.0% of all female hires) came straight from college; 5% of female WWII hires were taking care of children (Figure 11).

While most female hires did not stay with their WWII employer after the war, just 18.1% of female scientists left the labor force altogether. Most women, 37.2%, took jobs at universities or colleges after war. 26.6% found work at another firm, and 10.6% switched into the public sector (Figure 12).

Investigating the Identifying Assumption

A potential challenge to the identifying assumption is that enlistment may be correlated with traits of firms that influence research productivity. To investigate the identifying assumption, we first compare traits of exposed and control firms in 1939, the last year before the start of the WWII draft (Table 1). These comparisons reveal no differences in the prewar share of women in the firms' scientific staff, the number of female hires, or in publications and patents per scientist.

Exposed firms employ and hire more scientists in 1939. This difference is mechanical because the probability that at least one scientist enlists increases in the number of scientists employed by the firm. By the same logic, exposed firms employ more female scientists in 1939 - but do not differ in the share of women among scientists. While exposed firms have a higher stock of female scientists in 1939, they are not differentially likely to *hire* female scientists in 1939. Importantly, the number of scientists (Figure 13) and the number of female scientists (Figure 14) are not correlated with the *share* of enlisted scientists.

Since age determines eligibility for enlistment, scientists working for exposed firms are on average younger in 1939 (Figure 15), but there is no significant relationship between average age and research productivity before, during, or after WWII (Figure 16).

Firm fixed effects absorb these level differences in firm size and average age. Moreover, all results are robust to linear and non-linear controls for changes in the number of scientists and their average age.

Firms that hire female scientists between 1940 and 1946 also employ more male and female scientists in 1939 and hire more male scientists. Importantly, these firms do not differ from other firms in the prewar share of women among scientists and they are not differentially likely to hire women in 1939. Instead, firms with a higher share of enlisted scientists are significantly more likely to hire women *after* 1939.

There is also no correlation between firms' enlistment exposure and their research productivity before WWII. Scientists in exposed firms produce 0.222 publications per scientist in 1939, and scientists in other firms produce 0.238 publications per scientist ($p = 0.7291$). Scientists in exposed firms produce 0.236 patents per scientist compared with 0.205 patents per scientist in other firms ($p = 0.6814$). Moreover, there is no relationship between enlistment and the share of a firm's scientists who are inventors (Figure 17). Firms that hire women during WWII produce 0.231 papers and 0.288 patents per scientist in 1939. Other firms produce 0.229 papers ($p = 0.9861$) and 0.214 patents ($p = 0.5306$) per scientist.

Enlistment rates vary little across the larger disciplines with 13.7% for chemistry, and 12.7% for physics, 12.7% for geology, and 13.4% for botany (Figure 18), though the data are noiser for anatomy, anthropology, astronomy, sociology, and political science, which together account for less than 1% of scientists.

Controlling for draft eligibility based on marital status, gender, children, birth year and state, a scientist's research discipline does not predict enlistment (Figure 19). OLS estimates show that scientists employed in firms are not differentially likely to enlist in the war compared with other MoS (1956) scientists (Table 2, Column 1). There is also no significant difference in the enlistment rate of scientists depending on their prewar productivity, measured by publications. Scientists with prewar patents are less likely to enlist, but at 0.9p.p. the difference is small (Table 2).

Maximum likelihood random effects regressions estimate the share of enlistment variation that is due to differences in disciplines' random intercepts rather than to within-discipline noise around these intercepts. While a likelihood ratio test rejects that discipline effects are zero, differences across disciplines only account for 0.8% of

the total variance in enlistment.[9]

3. Productivity Effects

Did the inflow of female talent make US firms more productive? To investigate this question, we test whether scientists in firms with female hires produced more publications and patents per scientists compared with other firms.

Difference-in-Differences OLS Estimates

First, we estimate OLS event studies

$$\text{Research Productivity}_{jt} = \alpha_j + \phi_t + \sum_{t,t\neq 1939}^{T} \left(\mathbb{1}[T=t] \times \text{Female Hires}_j\right)\beta_t + \varepsilon_{jt} \quad (3)$$

where *Research Productivity*$_{jt}$ measures publications or patents per scientist at firm j in year t. Firm fixed effects α_j control for variation in research productivity across firms, and year fixed effects ϕ_t control for variation in research productivity, for instance due to scientific breakthroughs or fluctuations in business cycles that that affect all firms. Under the assumption that, in the absence of WWII, changes in the productivity of scientists would have evolved similarly for firms with and without female WWII hires, β_t estimates the causal effect of exposure to a female co-worker on the productivity of the research team. *Female Hires*$_j$ is an indicator for firms that hire at least one female scientist between 1940 and 1946. 63 firms hire at least one female researcher during WWII (7.4%).

Until WWII, firms with and without female WWII hires were on parallel productivity trends in terms of publications per scientist (Figure 20). After the start of the war, however, researchers begin to produce more papers per researchers in firms with female hires. In 1942, the first year in which treated firms employed significantly more women than other firms, firms that hired women produce one additional publication per every 9 scientists on their staff, an increase of 55.8% (p = 0.022). Estimates are positive but insignificant during the war years 1943-45, and increase from 1946 onwards. In 1946, firms that hired female scientists during WWII produced 36.7% (p=0.037) more publications per scientist than firms without female relative to the pre-war 1939 average. By 1948, this difference has increased to 64.5% (p = 0.015), and it grows further to 73.7% in 1950 (p = 0.029), 95.6% in 1952 (p = 0.010), before declining again to 51.3% in 1954 (p = 0.023), and 52.3% in 1956 (p = 0.023).

[9] We obtain precise estimates of discipline intercepts since we study more than 13,000 scientists to identify differences across 15 disciplines. However, even at the upper bound of the estimated 95% confidence interval, research disciplines explain at most 2.9% of total variation in enlistment.

OLS estimates of the average treatment effect on the treated firms show that firms that hired female scientists during WWII increase their publication output per scientist by 0.9 publications per year (Table 6, column 1), one additional paper per 11 employed scientists per year (+45.4%).

For patents per scientists, there were also no significant differences in productivity trends before the war (Figure 21). Notably, there are no differential changes in patenting for firms with and without female hires after the start of the war. The average treatment effect on firms that hired women is -0.016 patents per scientist per year (p = 0.71), suggesting that – on average – there was no positive effect of hiring women (Table 6, column 4).

These results are robust to limiting the sample to incumbent scientists who had been hired by their WWII employers before the war. Female hires increase the publications of incumbent scientist by 35.3% (Table 6, column 2). At the same time, there is no increase in patenting (Table 6, column 5). Excluding enlistments years 1940-1946, OLS estimates imply that female hires increase publications by 57.5% (Table 6, column 3) without affecting patents (Table 6, column 6).

Changes in productivity cannot be explained by changes in the size or the age composition of a firm's scientific staff. Controlling for the stock and flow of scientists, firms that hired women produce 0.08 additional publications per scientist per year after 1939 (Table 7, Column 2). Controlling separately for the size of research teams before and after 1939, firms that hired female scientists produce 0.10 additional publications per scientist per year after 1939 (Table 7, Column 4). There is no significant change in patenting (Table 8). Results are robust to controlling for the average age and average age squared of scientists.[10] Firms that hired women during WWII produced 0.09 additional publications per scientist per year (Table 9, Column 2). Controlling separately for the age structure of a firm's scientific staff before and after 1939, firms that hired female scientists produced 0.08 additional publications per scientist (Table 9, Column 4). Here as well, there is no change in patenting (Table 10).

Instrumental Variable Estimates

The key identification challenge in studying the effect of female hires on firms' research productivity is that firms that choose to hire women may be systematically different from firms that do not. For instance, firms that valued research more may have been more likely to hire female researchers in response to the shortage of male scientists.

[10] For these estimates, we impute average age in years in which firms do not employ any scientists to the mean age of scientists employed in all other firms in the same year. See Figure 22 for the evolution of the average age distribution across firms over time.

In that case, OLS may overestimate the true effects of female hires on the productivity of researchers in these firms. Alternatively, discriminatory firms that saw themselves forced to hire women may have placed them in less productive research environments, causing downward bias in OLS.

To investigate the direction and intensity of selection, we study firms with enlisted male scientists. These firms experienced a quasi-random shock in the scarcity of male labor, which we use as an instrument for firms that hired women. Importantly, enlistment is not correlated with firms' prewar research productivity, female hiring, and research focus (see Section 2).

The exclusion restriction requires that enlistment affects productivity only through hiring female scientists. Enlistment may trigger changes in the size or age composition of research teams. Reassuringly, estimates are robust to controlling for changes in the size and age of a firm's scientific workforce. Enlistment may also affect publications (and patents) per scientists by changing the number of scientists. Notably, only publications but not patents per scientists increase after 1939, suggesting that the observed increase is not mechanical. Moreover, publications (but not patents) per scientists also increase when we restrict the sample to incumbent scientists who already worked at their WWII firm before the war.

The firm-level enlistment shock is a strong and meaningful instrument for female hires. Firms' exposure to enlistment is strongly correlated with the probability that the firm hired women during WWII (with a Kleibergen-Paap F-statistic of 37.4). The first stage coefficient suggests that exposure to enlistment increases the probability that a firm will hire a female scientist by 12.5 percentage points.

We estimate the first-stage equation:

$$\mathbb{1}[\text{Women} > 0]_{j,t\in 1940,1946} = \psi \times \mathbb{1}[\text{Enlisted} > 0]_j + \zeta_j + \omega_t + \varepsilon_{jt} \tag{4}$$

where $\mathbb{1}[\text{Women} > 0]_{j,t\in 1940,1946}$ indicates firms that hire at least one female scientist during the war, between 1940 and 1946, $\mathbb{1}[\text{Enlisted} > 0]_j$ indicates firms with at least one enlisted male scientist, and all other variables are defined as above.

Using two-staged least squares, we estimate the first stage jointly with the second-stage equation:

$$\text{Research Productivity}_{jt} = \mu \times \mathbb{1}[\text{Women} > 0]_{j,t\in 1940,1946} + \zeta_j + \omega_t + \varepsilon_{jt} \tag{5}$$

where *Research Productivity*$_{jt}$ measures publications and patents per scientist in firm j in year t.

IV estimates confirm that hiring female researchers increased research productivity in terms of publications. In firms that hired female scientists during WWII research productivity increased by 0.418 publications per scientist and year (Table 11, p = 0.004). Relative to a pre-war mean of 0.239, this implies an 174.6% increase. For patenting, however, estimates are much smaller, at 0.066, the point estimate for patents per scientist per year is significantly smaller and not statistically significant.

Consistent with downward bias, IV estimates are 4.6 times larger than OLS estimates. If firms systematically place women in weaker research teams, this selection effect would result in downward bias in the OLS estimate. At the same time, women who are hired exogenously to replace enlisted male scientists may have a particularly high local average treatment effect on the marginal research team that urgently required a new co-worker.

To rule out that the productivity increase is attributable to mechanical correlation between male scientists' enlistment and the productivity of research teams, we rerun the analysis focused on the productivity of incumbent researchers who remain at the firm and are exogenously provided with a new female co-worker. We find that incumbent scientists in firms that hire women during WWII increase their research productivity significantly. IV estimates show that incumbents in firms with enlisted scientists produce on average 0.322 additional papers per year after the start of WWII (Table 13, column 2). We do not find a significant effect on incumbents' patenting output (Table 13, column 4).

IV estimates that restrict treatment to drafted scientists show that scientists at firms with female WWII hires 0.321 more publications per year after 1939, without a significant change in patenting (Table 4).

Changes in productivity are robust to control for the size or the age composition of a firm's scientific staff. Controlling for the stock and flow of scientists, firms that hired women during WWII produced 0.442 additional publications per year (Table 14, Column 3, p = 0.008) but only 0.079 additional patents (Table 15, Column 3, p = 0.753). Estimates controlling separately for the size of research teams before and after 1939 show that scientists in firms that hired women produced 0.520 additional publications per year (Table 14, Column 4, p = 0.006) but only 0.109 additional patents (Table 15, Column 4, p = 0.691). Results are robust to controlling for the average age and average age squared of scientists. Scientists in firms that hired women produced 0.416 additional publications per year (Table 16, Column 3, p = 0.005) but only 0.082 additional patents (Table 17, Column 3, p = 0.713). Controlling separately for the age composition of a firm's scientific staff before and after 1939, firms that hired women produced 0.377 additional publications (Table 16, Column 4, p = 0.010) but only 0.031

additional patents per year (Table 17, Column 4, p = 0.889).

Within Firm-Analysis for DuPont, GE, American Cyanide, and Shell

Next, we investigate variation across disciplines within firms across the largest employers of female scientists during WWII (Figure 23): DuPont de Nemours & Company (DuPont), General Electric Company (GE), American Cyanamid and its pharmaceutical division Lederle Laboratories (Lederle Labs), and Shell Oil (Shell).[11] The size and breadth of research topics in the work force of these firms allow us to investigate variation in exposure to enlistment and female hires across research teams and use this variation as an instrument for female hires within the same firm. DuPont employs 2,338 scientists, GE 1,110, Lederle 512, and Shell 327 scientists. At DuPont, 15.7% of male scientists enlist, 14.3% at GE, 14.0% at Lederle, and 14.2% at Shell. Du Point hired 30 women to replace 363 men (8.3%), while Lederle hired 19 women to replace 69 men (27.5%, Table 18). DuPont hired the largest number of women during the war, up from 2 women in 1939 to 14 women in 1944, Figure 24), while Shell experienced the largest increase in the share of women (from 2.3% in 1939 to 6.9% in 1943, Figure 25).

Even within firms, exposure to enlistment is highly correlated with an increase in female hires during WWII. The raw data of enlistment and female hiring show that research teams within these four teams are significantly more likely to hire women if they are exposed to enlistment. The slope coefficient from regressing female hires on the number of enlisted men is 0.09 (p = 0.00, Figure 26).[12] Event study estimates at the level of the research team confirm that teams exposed to enlistment were as likely to hire women as other departments before 1939 but significantly more likely to hire women after 1939. Research teams that were exposed to enlistment on average hired 0.15 additional women in 1940, 0.30 in 1941, 0.26 in 1942, 0.30 in 1943, and 0.33 in 1944. Event study coefficients after 1944 are insignificant (Figure 27). The average treatment effect on research teams exposed to enlistment corresponds to 0.12 more female hires per year after 1939 than other research teams (p = 0.045).

Next, to estimate the causal effect of female hires on research team productivity within these four firms, we estimate instrumental variables regressions. Specifically, we estimate regression specifications as in Eq. 4 and 5 above with research teams as the unit

[11] While the scientists in our data partly work for different subsidiaries of these companies (e.g. Shell Chemical Company), we link them to common firm identifiers at the level of the respective conglomerate. This way, we are able to trace scientists' employers even if there is variation in the legal and organizational structure of these firms.

[12] The slope coefficient increases to 0.11 (p = 0.00) when excluding the largest research team, chemistry at DuPont (313 enlisted men, 27 female hires).

of observation. We first estimate a pooled IV specification across the four firms and then separate IV regressions for each firm, using variation in which research teams within the firm are exposed to enlistment and comparing them with other research teams within the same firm. The pooled IV specifications for publications (Table 19) and patents (Table 20) confirm the result that female hires increased publications per scientist at US firms after 1939 but did not have a significant effect on the number of patents per scientist. Consistent with the results for all firms, we find that enlistment is a strong and meaningful instrument for female entry. Research teams exposed to enlistment are 40 percentage points more likely to hire women than other research teams after 1939, first-stage strength is high with a Kleibergen-Paap F-statistic above 248. TSLS estimates suggest that adding women to a research team at DuPont, GE, Lederle or Shell increases the publication output of the team by about 0.230 papers per scientist per year – about one additional publication per 5 scientists. Similar to IV results for the full sample of firms, we find that OLS estimates of the productivity effect are biased downwards.

Separate IV estimates for the four firms reveal significant heterogeneity in the productivity effects of female hires across firms. Specifically, we observe that female hires increase publications per scientist per year in research teams at Lederle and Shell but we do not observe significant effects on publications at DuPont at GE. IV estimates of the effect of female hires on patents per scientist per year show that female hires significantly increase patent productivity at Lederle, do not significantly affect patents per scientist and year at GE and Shell, and significantly decrease patent productivity at DuPont.

4. Mechanisms

Why did scientists become more productive in firms that hired female scientists during WWII? We investigate selection, knowledge spillovers and the tasks that women performed within firms.

Women are Positively Selected

Working with high-ability researchers may increase the productivity of their co-workers, and women in science may be positively selected if they face barriers to entry or other gendered distortions in occupational choice (Hsieh et al. 2019; Lubczyk and Moser 2025).

Consistent with positive selection, we find that female scientists are more likely to have a PhD or an elite (Ivy Plus) education: 72% of female scientists have a PhD,

compared with 66% of men, and 35% have an Ivy Plus degree, compared with 27% of men. Female scientists also produce more highly cited patents and publications (Lubczyk and Moser 2025). Faced with significant career penalties of children (Kim and Moser 2025), just 26% of female scientists in US firms have children, compared with 79% of male scientists, and only 46% are married, compared with 89% of men.

Women Contribute Novel Ideas

In addition to being positively selected, women may increase the productivity of their male coworkers by contributing novel perspectives and ideas. To investigate this mechanism, we use the text that describes each scientist's research to compare the novelty of research by male and female WWII hires relative to the incumbent scientists at the firm.

Kernel density estimates show that the novelty distribution of female hires is shifted to the right of the distribution of male hires (Figure 28). The median female hire's research has a firm-specific novelty score of 0.260 compared with 0.237 for the median male hire. The difference rises towards the tail of the distribution: at the 90th percentile, female hires have a novelty score of 0.418 compared with 0.355 for male hires.[13] Female hires contribute more novel research than men at every quantile (Figure 29).

OLS estimates show that this result is robust to controlling for the traits of scientists and employers. The research of female hires is significantly more novel to their employers than that of male hires at the same firm, of the same age, and in the same research field (Table 23). Estimates are robust to measuring novelty as distance to the firm centroid rather than averaging over incumbents (Table 24).

Men Write More on Their Own and with Other Men

To examine spillovers, we study co-authoring between male and female scientists. Male scientists in US firms may become more likely to work with women after 1939 because they have more female colleagues or because they might update their beliefs about women's productivity.

Do male scientists co-author more with women after 1939? To conduct this analysis, we study collaboration between co-workers, when two scientists collaborate on a paper while they are employed by the same firm. Specifically, we estimate two-way fixed effects OLS regressions of male scientists' co-authoring in firms that hired women

[13]Novelty measures the angular distance between scientists in the research keywords-space. Because keyword vectors vary in length and weights, differences are best interpreted as distance in topic mass. Interpretation is simpler for vectors of equal length with binary weights: in this case novelty measures 1 minus the share of keywords that overlap.

during WWII compared with men in other firms before and after the start of the war.[14]

OLS estimates confirm that increases in research productivity were mainly driven by male scientists producing more papers per year and men co-authoring more with their male co-workers (Table 25). We find that male scientists publish 0.097 more papers per year in firms that hired women after 1939, a 49.2% increase relative to 1939. We also find that male scientists produce 0.021 additional co-authored publications with their male coworkers, a 106.2% increase. In contrast, we find no significant change in male scientists' co-authored publications with their female coworkers or other female scientists. Specifically, male scientists increase their publication output in firms that hired female scientists as researchers. In these firms, male scientists published 0.121 more papers per year and 0.025 additional papers with their male co-workers than researchers in firms that did not hire women during WWII.

This result is consistent with a "Matilda effect" (Rossiter 1982, , after Matilda Joslyn Gage's 1893 essay "Woman as Inventor") of female hires increasing the productivity of male scientists without receiving credit. Prominent examples of "Matildas" in the MoS (1956) include Esther Lederberg, a microbiologist who discovered the lambda phage, Helen B. Taussig, a cardiologist who co-invented the "blue baby" heart surgery, Mildred Cohn, a biochemist studying enzymes using nuclear magnetic resonance, and Gerty Cori, a biochemist working on carbohydrate metabolism.

Talent Misallocation within the Firm

Even if firms hired female scientists during WWII, many women were pushed into sex-typed jobs within firms, such as librarianship, literature research, or technical writing (Rossiter 1995). Else Schulz of Procter and Gamble described perceptions of women's aptitude for librarian tasks in 1945 (Rossiter 1995, p.262):

> "The work offers wide opportunity especially to the women chemist, because women, by nature, are usually good at detail work, interested in wiring, and equipped with the curiosity, intuition, and patience needed to hunt for and find facts."

Data on the job titles of female scientists at US firms confirm this prediction: 68.3% of research librarians employed during WWII are women. Women who worked as research librarians were highly qualified, typically holding PhD degrees. Compared with other female scientists they were, however, less likely to have elite education from Ivy plus institutions. Elizabeth Burkey, for example, completed her PhD in chemistry

[14] For most firms in our sample, women hired during WWII were the first female scientists they employed. Accordingly, we cannot observe prewar trends for the productivity of female scientists at these firms.

at Rochester in 1940, worked as an instructor at Wells College, and in 1941, she was hired by DuPont as a literary chemist and librarian in the electrochemical department. She stayed with DuPont until the end of the war in 1946. After WWII, Burkey found employment as an assistant professor of chemistry.

BURKEY, DR. ELIZABETH H(UGHES), 2016-C Lorraine Road, Reading, Pa. ORGANIC CHEMISTRY. Newark, N. J. April 12, 13 A.B, Mt. Holyoke Col, 34; Ph.D.(chem), Rochester, 40. Instr. chem, Wells Col, 39-41; Mt. Holyoke Col, 38-39; library chemist and librarian, electrochem. dept, E. I. du Pont de Nemours & Co, Inc, 41-46; instr. and asst. prof. CHEM, Hollins Col, 48-53; ASST. PROF, ALBRIGHT COL, 53- Chem Soc.

The same data show that WWII temporarily narrowed the gender gap in scientific leadership positions. Between 1930 and 1939, 6.2% of female scientists occupy leadership positions in firms as directors, managers, section heads or supervisors compared with 24.9% of male scientists. As women are drawn into firms during the war, the share of women in leadership positions rapidly increases up to 17% in 1940 but then declines back to 9% in 1943-44. By 1944, the gender gap in leadership positions has returned to its prewar level (Figure 30). In total, the share of women among scientists in leadership positions increases from 0.2% in 1937 to 0.7% in 1942 and remains at that level throughout the 1940s and 1950s (Figure 31). The share of women among scientists in research roles increases from 1.1% in 1937 to 2.8% in 1943 but then gradually declines.

Examining job titles at DuPont, GE, Lederle, and Shell, we observe that Lederle – the only firm to experience positive productivity effects from hiring women in both publishing and patenting – was most likely to hire women in leadership positions. Specifically, 26.1% of female scientists hired at Lederle were employed in leadership positions, compared with 26.5% of male scientists. Women were much less likely to be in leadership positions at the other three firms: GE hired 10.5% of women for leadership roles compared with 18.3% of men, DuPont hired 6.9% of women for leadership roles compared with 28.4% of men, and Shell did not hire any women into leadership compared with 14.3% of their male scientific staff.

In contrast, DuPont – the firm to experience the smallest productivity increase from hiring women – was most likely to employ these women as librarians or assistants. 21.9% of female hires at DuPont were employed in librarian and assistant roles, compared with 9.4% of male scientists. The other firms employed a lower share of their female scientific staff as librarians or assistants: GE assigned 7.4% of women to these roles compared with 7.0% of men, Lederle assigned 13.8% of women compared

with 10.5% of men, and Shell assigned 12.3% of women compared with 10.0% of men.

Women are less likely to be hired in leadership roles and they may also be less likely to achieve them through promotions (Babcock, Recalde, Vesterlund, and Weingart 2017). To investigate gender differences in each scientist's probability to receive a promotion, we estimate OLS regressions for scientists who work in research roles and stay with the same firm for at least two years:

$$\text{Leadership}_{i,j,t+1} = \delta \times \mathbb{1}[\text{Female}]_i + \mathbf{X}'b + \varepsilon_{i,j,t} \tag{6}$$

where $Leadership_{i,j,t+1}$ indicates whether scientist i is promoted to a leadership position at firm j in year $t+1$, $\mathbb{1}[\text{Female}]_i$ indicates female scientists, and $\mathbf{X}$ is a vector of explanatory variables. The vector $\mathbf{X}$ includes three sets of explanatory variables: First, we control for performance measured by the number of patents and publications produced by scientist i in year t. Second, we control for experience by including birth year fixed effects as well as the number of years scientist i has been employed in firm j and its square. Third, we control for the specific workplace context by including year fixed effects, firm fixed effects, and field fixed effects (at the level of the volumes of MoS (1956)).

OLS estimates show that women are significantly less likely to be promoted from research to leadership roles (Table 27). The unconditional gender promotion gap is 56.0%. Even when accounting for performance, experience, and job tenure, women are 36.9% less likely to be promoted. Notably, our data suggest that patenting – which male scientists are significantly more likely to do than female scientists – is a promotable task, while publishing – where we observe productivity effects from hiring female scientists – is not. Scientists who produce at lease one patent are 22.3% (p = 0.010) more likely to be promoted. Scientists who produce at least one publication are just 11.4% (p = 0.098) more likely to be promoted.

5. Conclusions

This paper studies the productivity effects of increasing female representation in science. We exploit a linkage of scientists' biographies with the firms that employ them to show that underrepresented female hires have a positive effect on firms' publication productivity but not innovation. Empirically, we use exogenous variation from the WWII draft when the shortage of male scientists forced US firms to hire female scientists.

We have found that firms that were exposed to enlistment during WWII hired 1.4 times more female scientists during the war. Firms that hired at least 1 female scientist

produced 1 additional publication per 11 employed scientists after the war - but no additional patents.

Examining the mechanisms behind these results, we have found that the productivity effects of female hires vary significantly across firms. Firms that placed women in leadership roles experienced greater gains in research productivity. We have found that the increase in publications is mainly driven by male scientists co-authoring with their male co-workers. We have also found that female scientists at US firms are positively selected and contributed novel research topics to their employers. Women, however, were mainly placed in sex-typed jobs such as research librarians. Our findings suggest that a misallocation of talent *within* firms diminished the productivity gains from hiring women.

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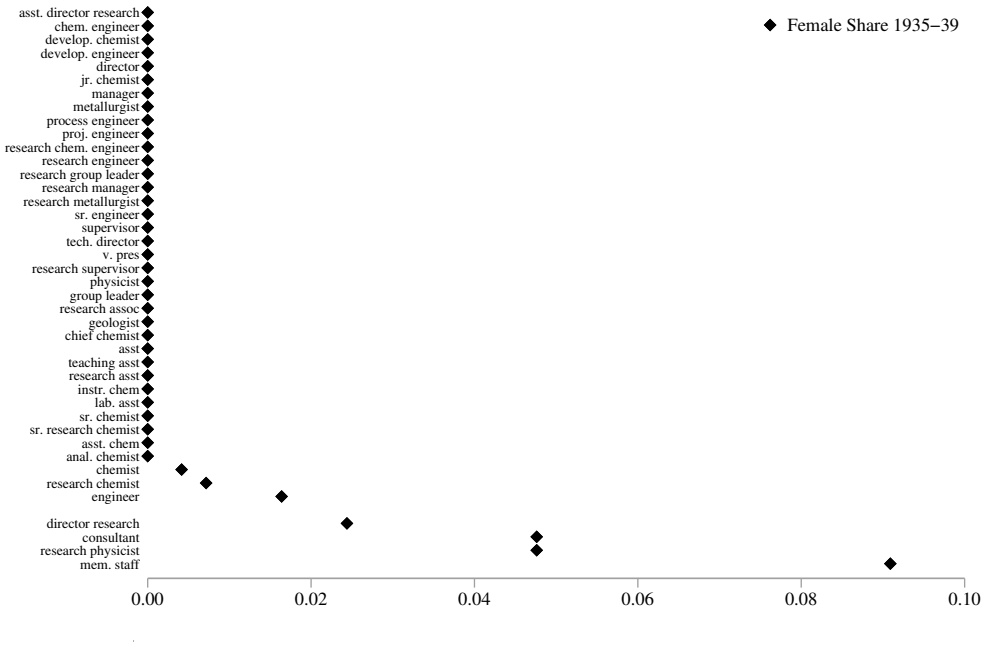
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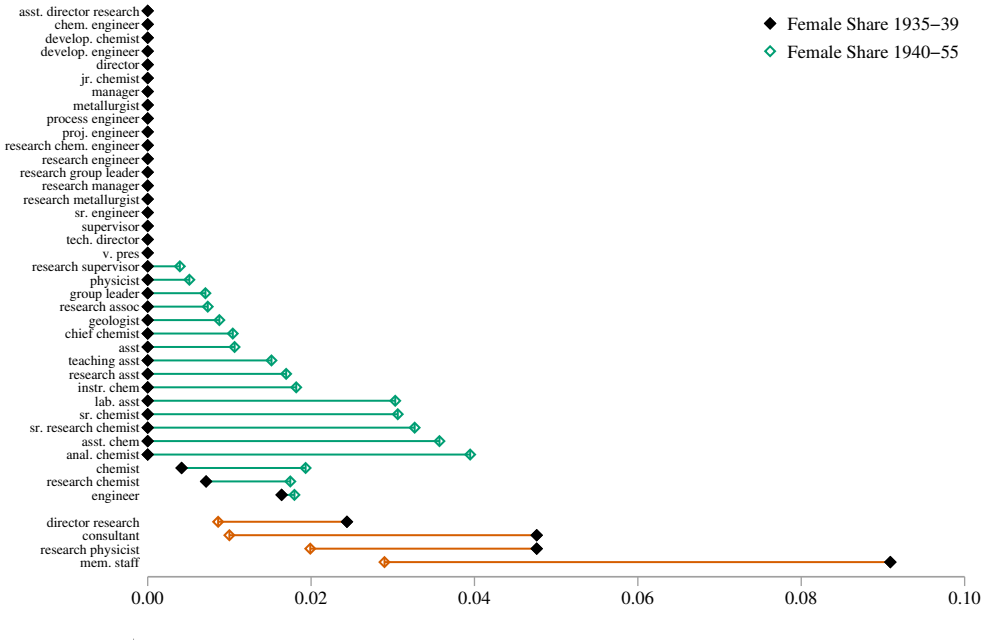
6. FIGURES

Figure 1: Job Titles and Female Participation, 1935-39



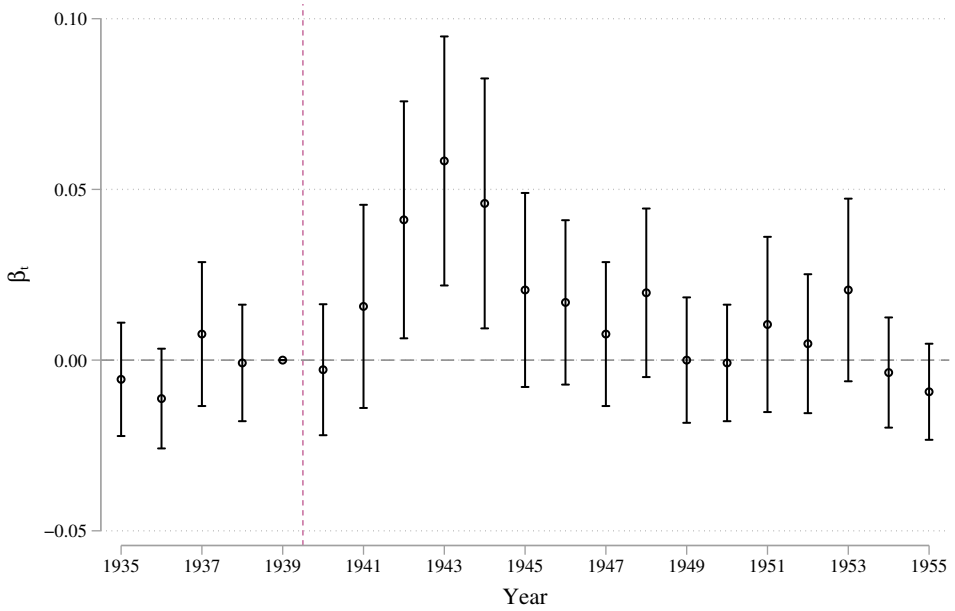
Note: Pre-WWII share of women among all scientists in the 42 most common job titles for scientists in firms. Job titles are included if they are held by at least 50 different scientists in MoS (1956).

Figure 2: Job Titles and Female Participation, 1935-55



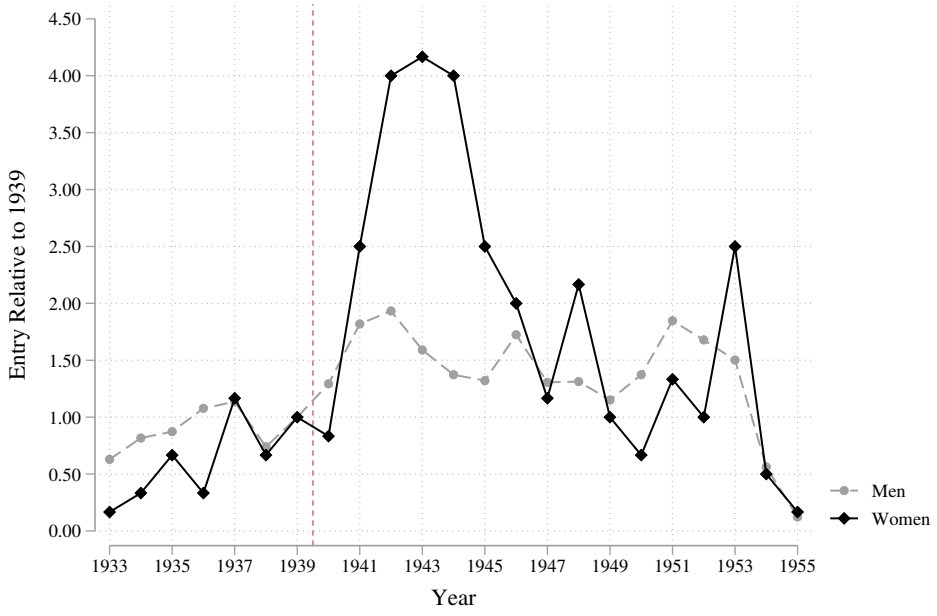
Note: Pre- and post-WWII share of women among all scientists in the 42 most common job titles for scientists in firms. Job titles are included if they are held by at least 50 different scientists in MoS (1956).

Figure 3: Event Study: Female Entry into Firms Exposed to Enlistment



Note: Point estimates and 95% confidence intervals for OLS estimates of Female Entry$_{jt} = \alpha_j + \phi_t + \sum_{t,t\neq 1939}^{T} \left(\mathbb{1}[T=t] \times \text{Enlistment}_j\right)\beta_t + \varepsilon_{jt}$. Standard errors clustered at the firm level.

Figure 4: Male and Female Scientists Hired at US Firms



Note: Indexed entry cohort size for male and female hires at US firms.

Figure 5: Stock of Female Scientists at US Firms

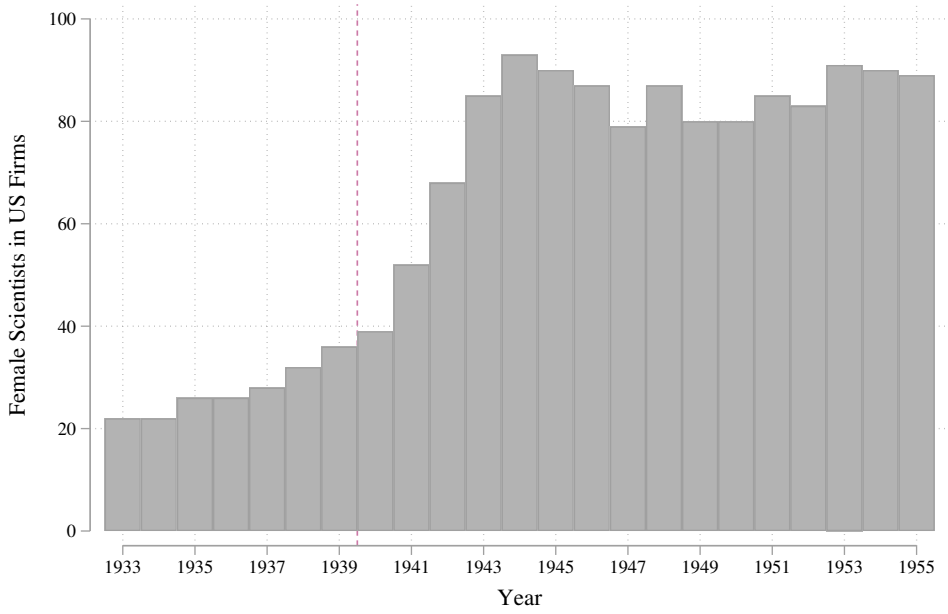


Figure 6: Share of Women among Scientists at US Firms

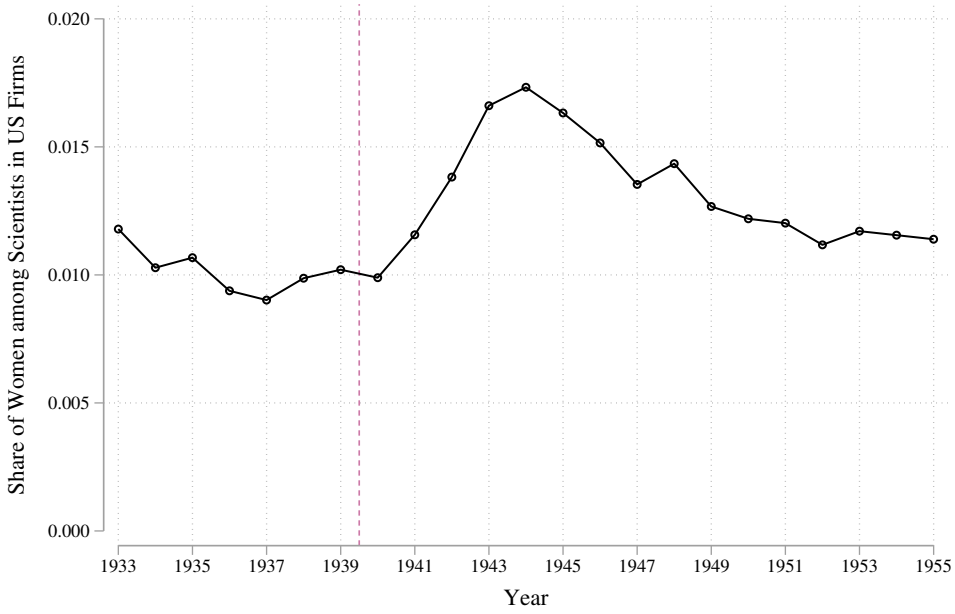
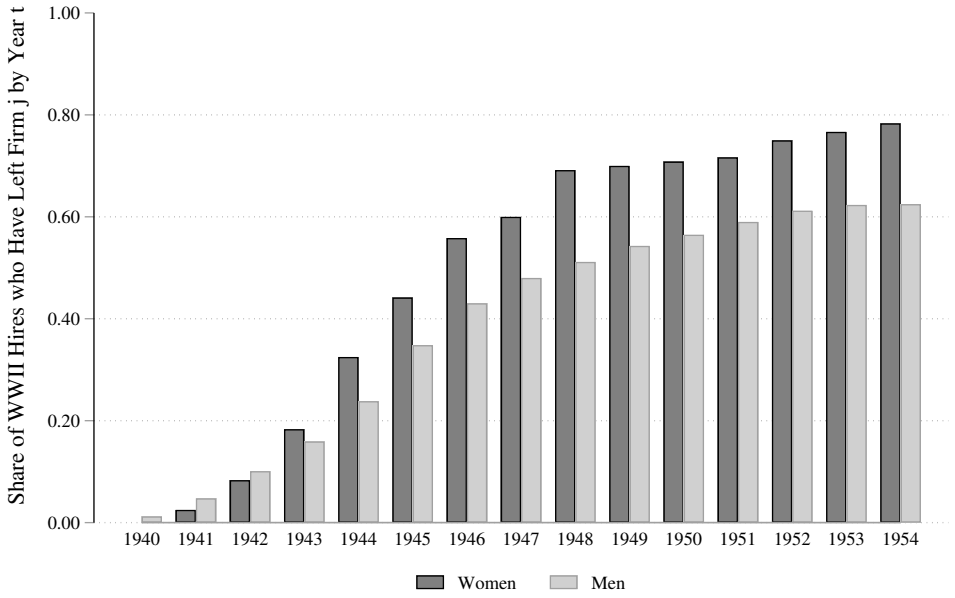
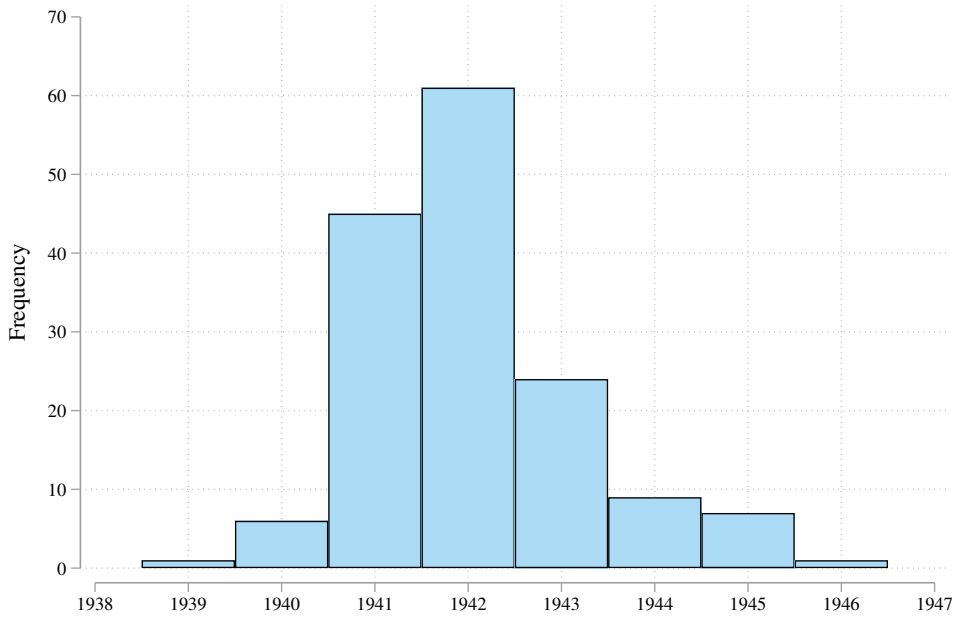


Figure 7: Employment Duration at First WWII Employer



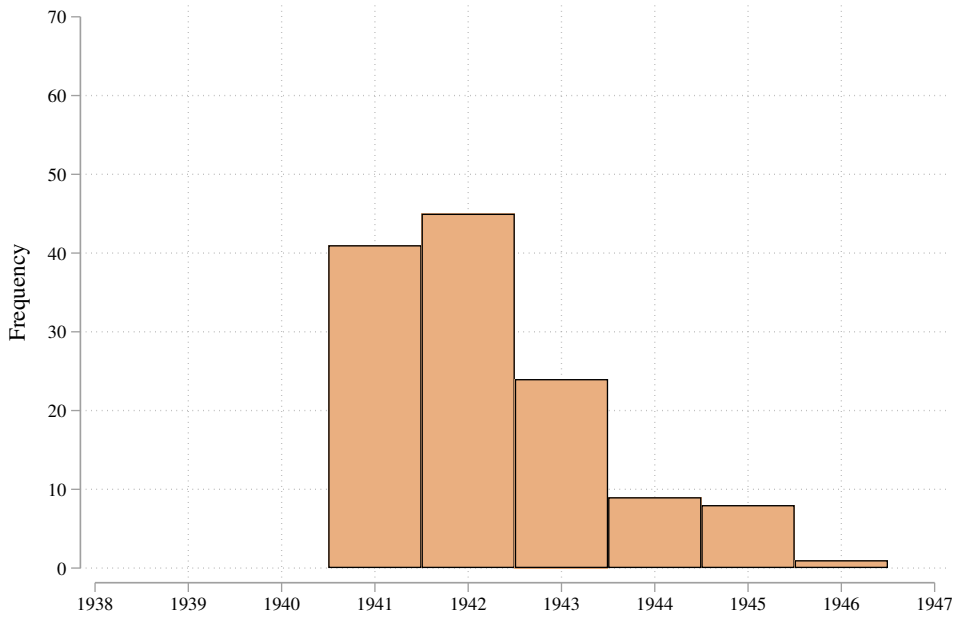
Note: Share of scientists who have left the firm that first employed them during WWII.

Figure 8: Staggered Exposure: Enlistment



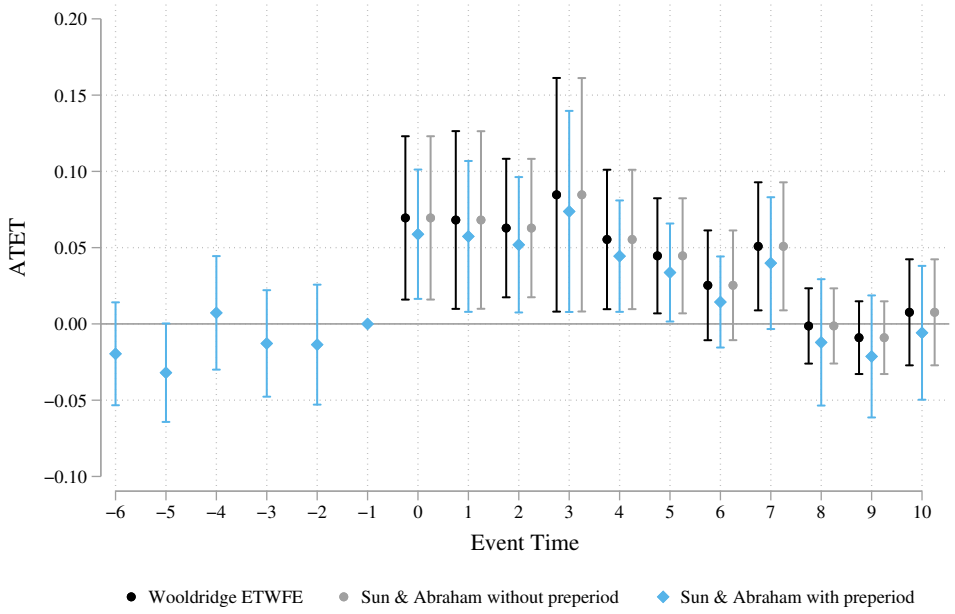
Note: Year of firms' first exposure to enlistment. 154 firms are directly exposed to the enlistment of a scientist they employed immediately before enlistment.

Figure 9: Staggered Exposure: Draft



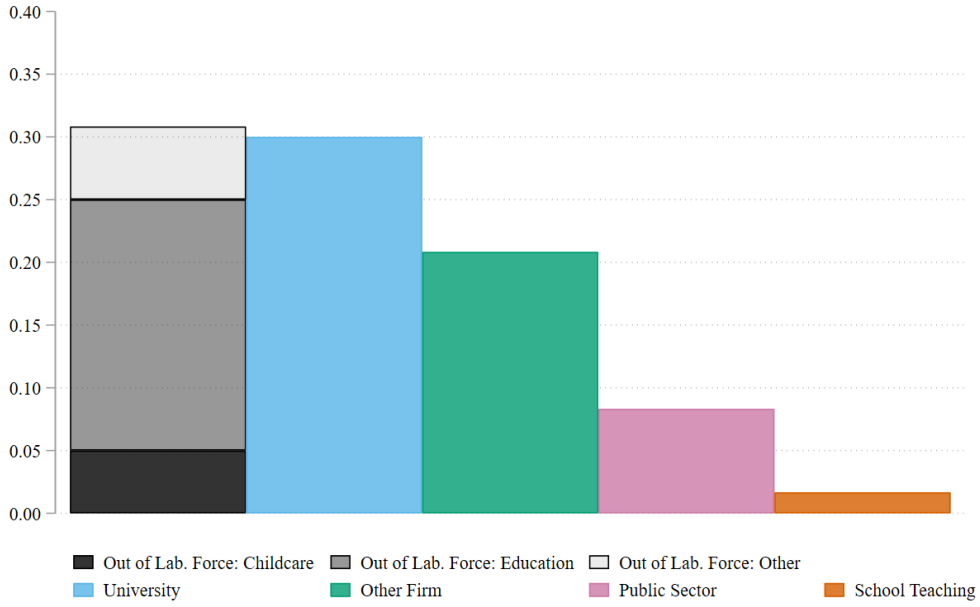
Note: Year of firms' first exposure to the draft. 128 firms are directly exposed to the enlistment of a scientist they employed immediately before the scientist was drafted.

Figure 10: Staggered Exposure Event Study



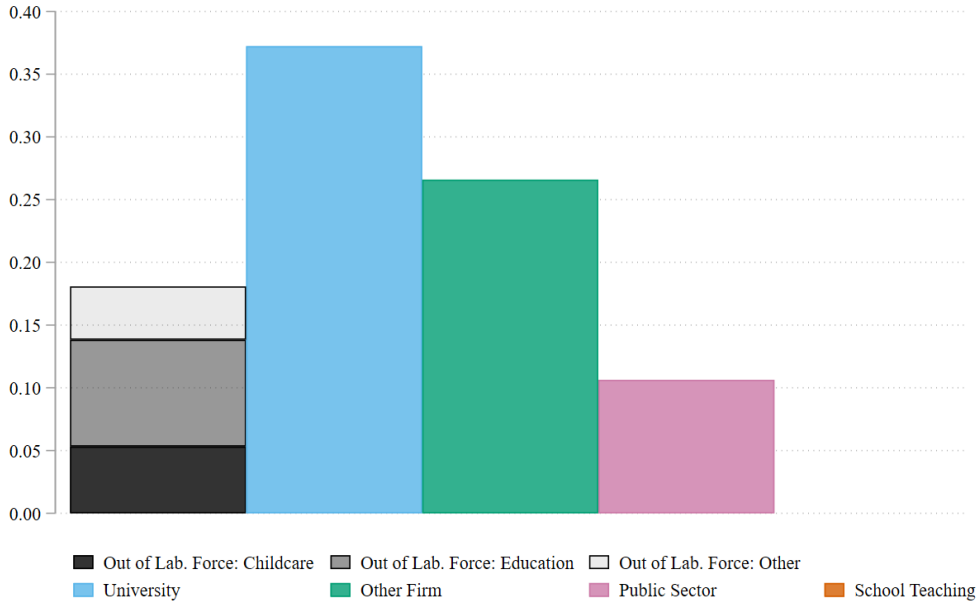
Note: Treatment defined as staggered exposure to enlistment.

Figure 11: Last Prewar Employment for Female Scientists Hired During WWII



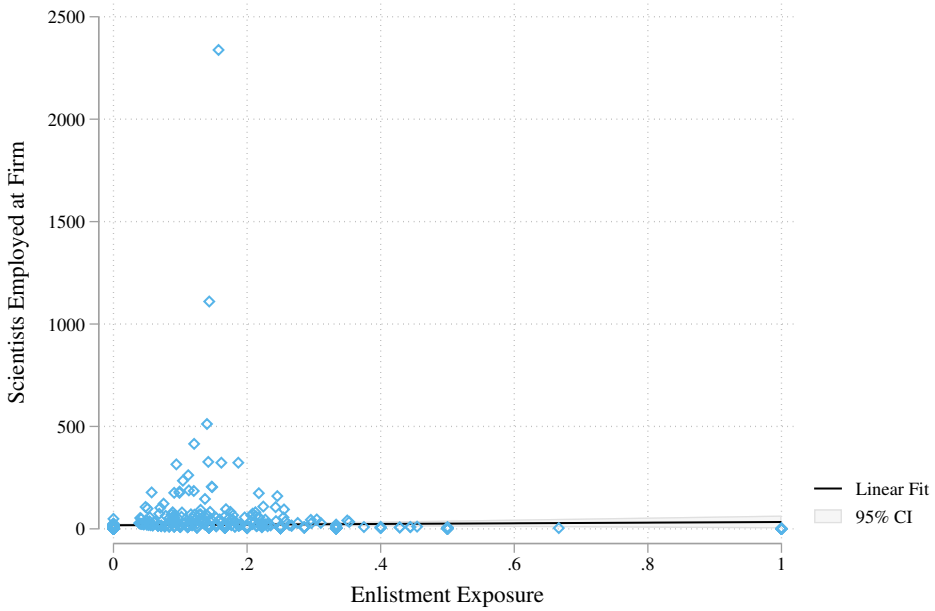
Note: Female scientists hired by US firms during WWII by employer type in their last prewar employment spell.

Figure 12: First Postwar Employment for Female Scientists Hired During WWII



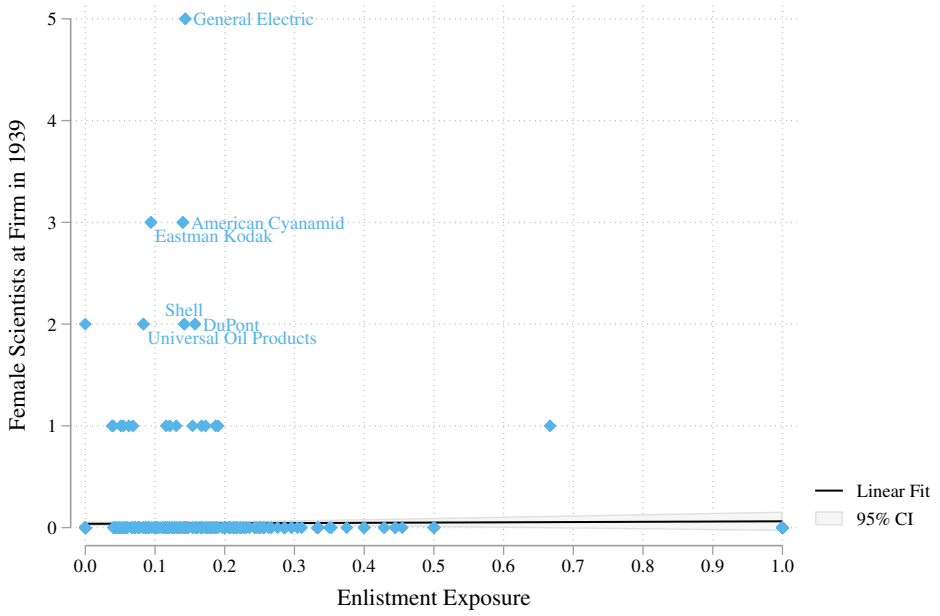
Note: Female scientists hired by US firms during WWII by employer type in their first postwar employment spell.

Figure 13: Enlistment Exposure and Firm Size



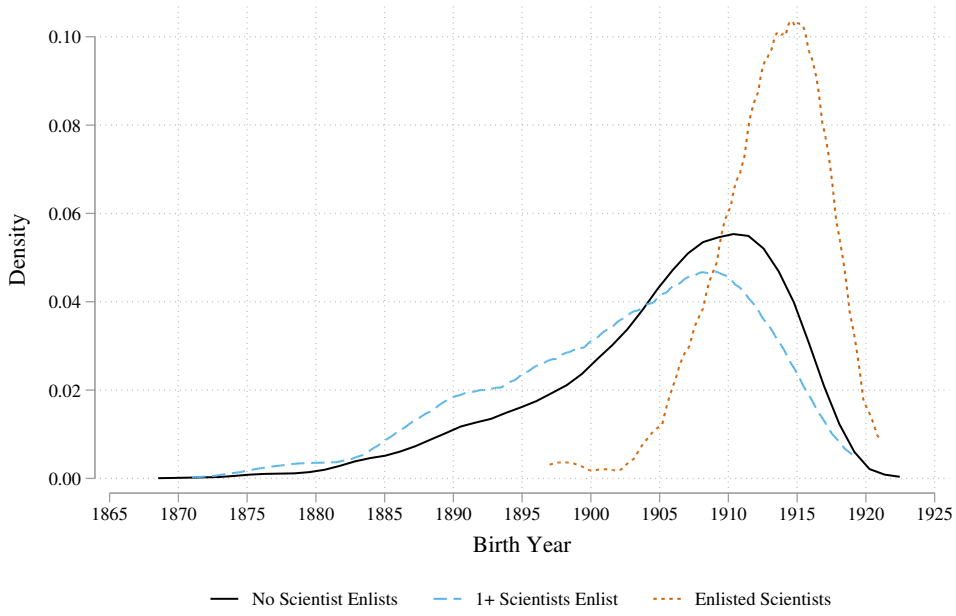
Note: Share of enlisted scientists plotted against total number of employed scientists. Correlation = .

Figure 14: Firm-Level Enlistment Exposure and Female Representation



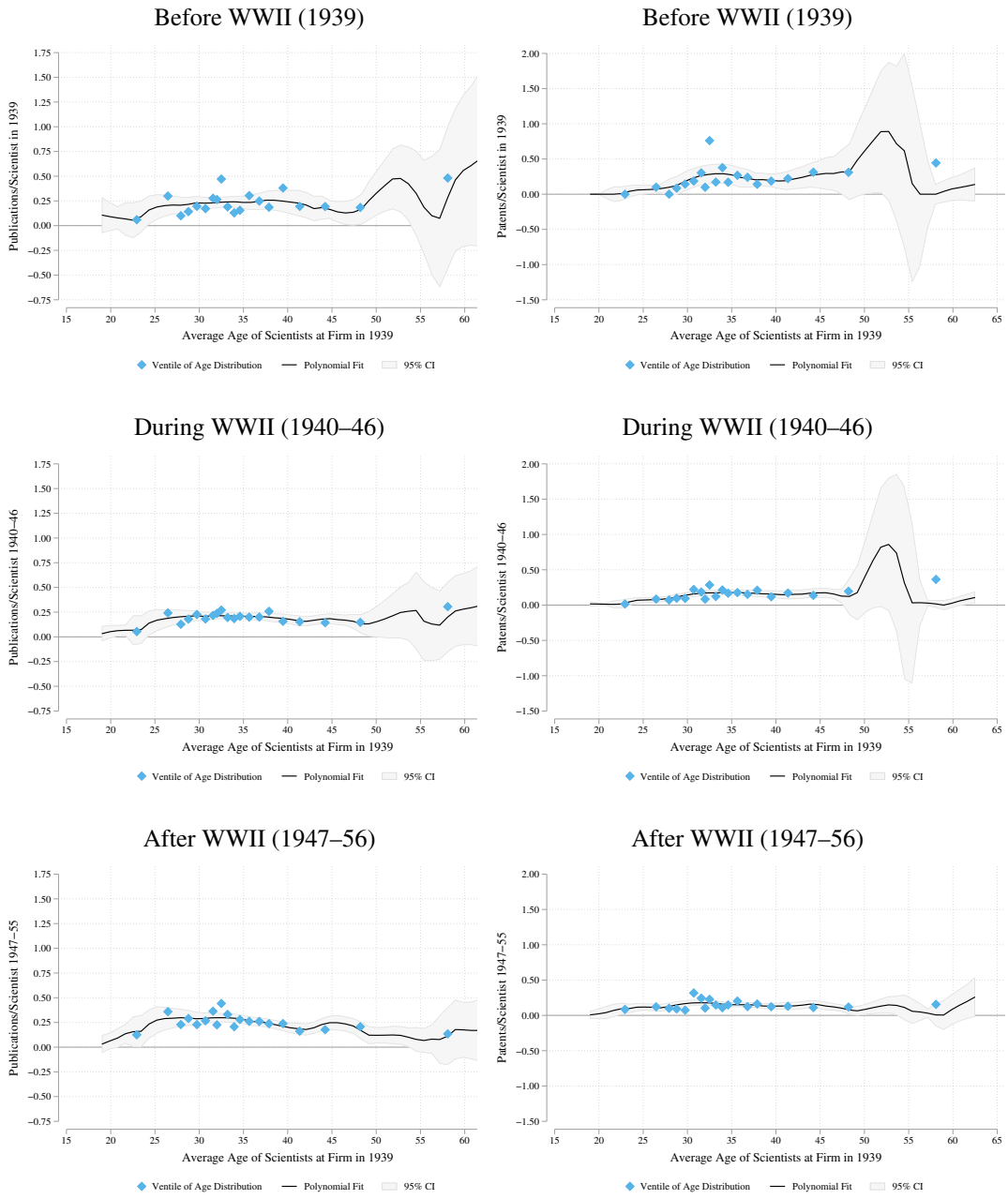
Note: Share of enlisted scientists plotted against female scientists in 1939. Correlation = 0.025 (p = 0.290).

Figure 15: Birth Year Densities for Scientists Employed in 1939



Kernel density estimates of birth year distributions for firms exposed to enlistment, other firms, and enlisted scientists. Sample limited to firms' 1939 employees.

Figure 16: Average Age of Scientists at Firm in 1939 and Research Productivity Before, During, and After WWII



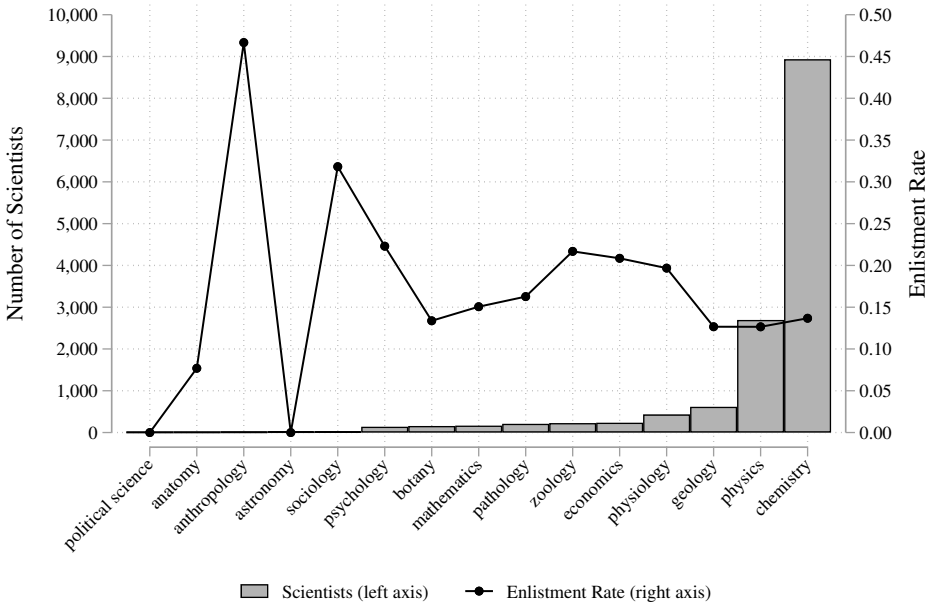
Binned scatter plot of average age of scientists at each firm in 1939 and research productivity before, during, and after WWII. Age distribution across firms aggregated to 20 bins and overlaid with polynomial.

Figure 17: Enlistment Exposure and Firm Innovativeness



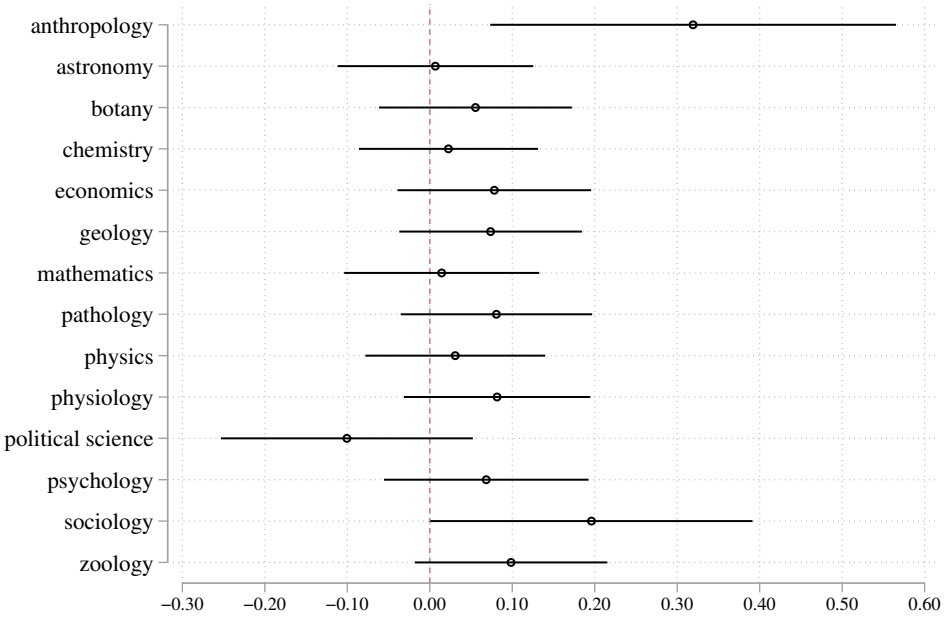
Note: Share of enlisted scientists plotted against share of scientists with at least 1 patent. Firms that employ 2 or more scientists. Correlation = -0.12 (std. error = 0.08).

Figure 18: Variation in Enlistment Rates across Disciplines



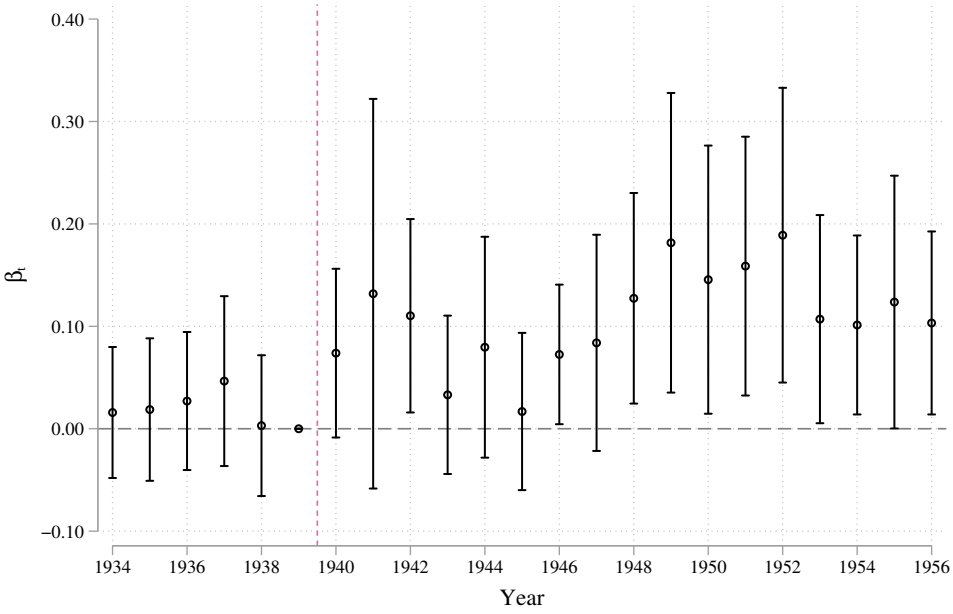
Share of enlisted scientists across research disciplines. Bars sorted by the number of scientists in discipline.

Figure 19: OLS Predictions of Enlistment with Research Discipline Dummies



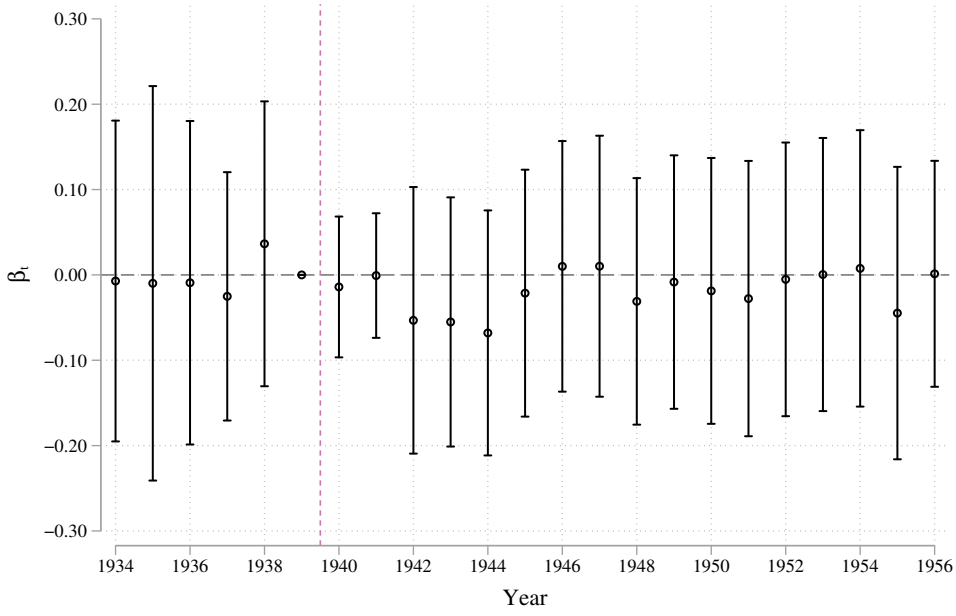
OLS coefficients for research discipline fixed effects with 95% confidence intervals for a prediction of $Pr(Enlisted)_i$. Enlistment is a binary variable. Specification further includes control variables for marital status, gender, parenthood, birth year, birth state fixed effects. Anthropology and sociology jointly account for fewer than 0.3% of scientists in our data.

Figure 20: Event Study: Publications per Scientist



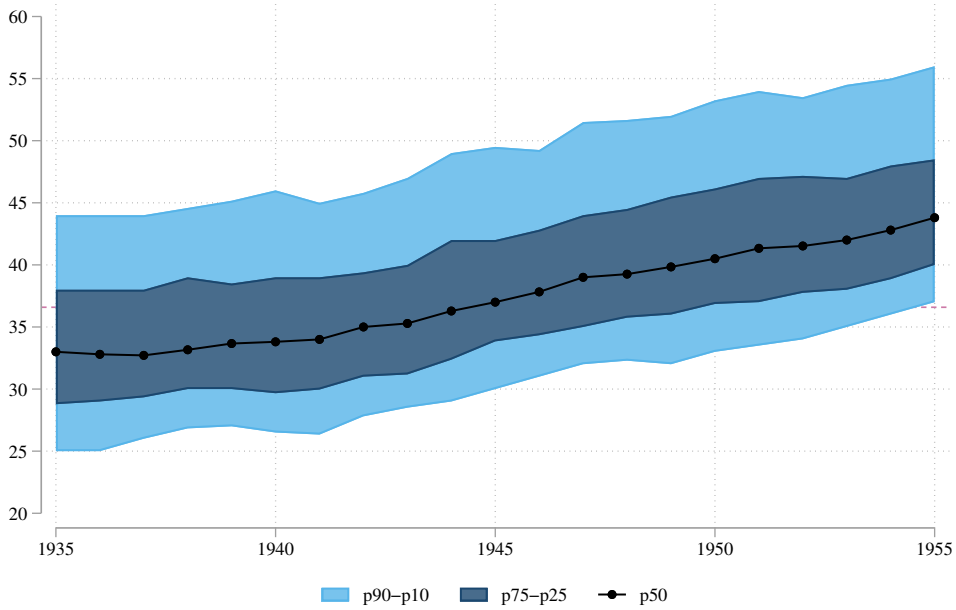
Note: Point estimates and 95% confidence intervals for OLS estimates of Research Productivity$_{jt} = \alpha_j + \phi_t + \sum_{t,t\neq 1939}^{T} \left(\mathbb{1}[T=t] \times \text{Female Hires}_j\right)\beta_t + \varepsilon_{jt}$. Standard errors clustered at the firm level. Research productivity measured as publications per scientist.

Figure 21: Event Study: Patents per Scientist



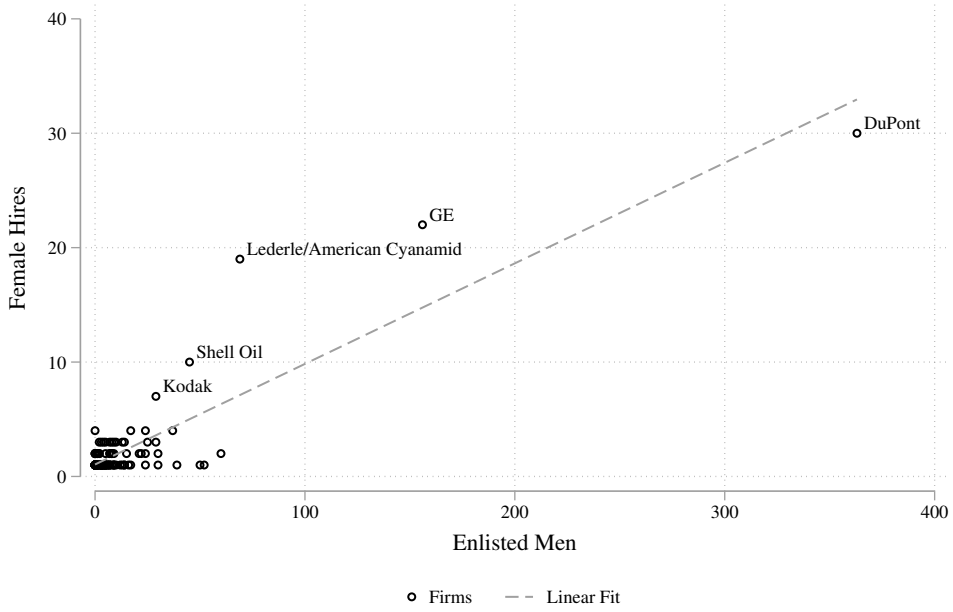
Note: Point estimates and 95% confidence intervals for OLS estimates of Research Productivity$_{jt} = \alpha_j + \phi_t + \sum_{t,t\neq 1939}^{T} \left(\mathbb{1}[T=t] \times \text{Female Hires}_j\right)\beta_t + \varepsilon_{jt}$. Standard errors clustered at the firm level. Research productivity measured as patents per scientist.

Figure 22: Distribution of Average Age among Employed Scientists over Time



Note: Distribution of average age of employed scientists across firms over time.

Figure 23: Enlistment and Female Entry at US Firms



Note: Headcounts of female entry and enlisted male scientists at US firms.

Figure 24: Female Scientists at 4 Largest Employers

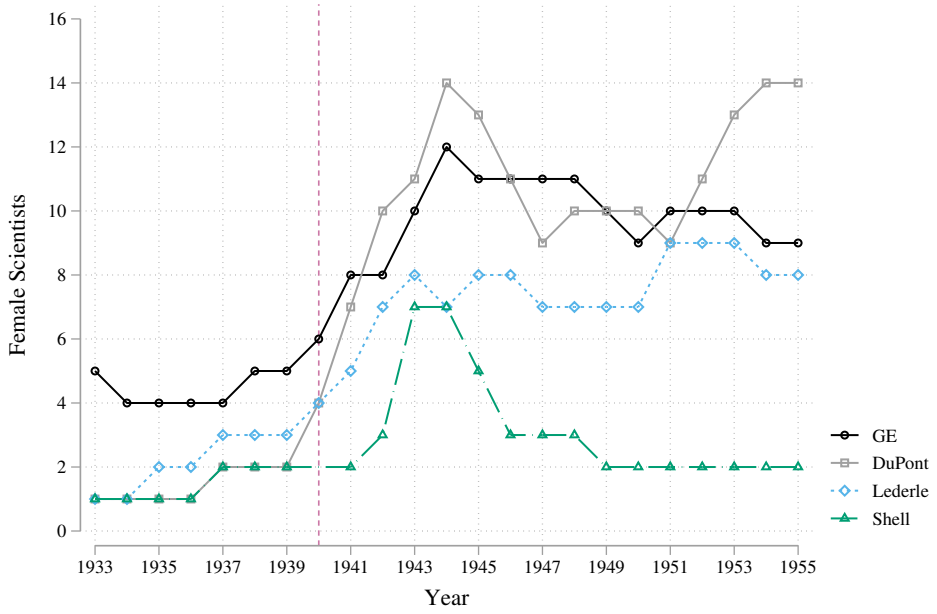


Figure 25: Share of Female Scientists at 4 Largest Employers

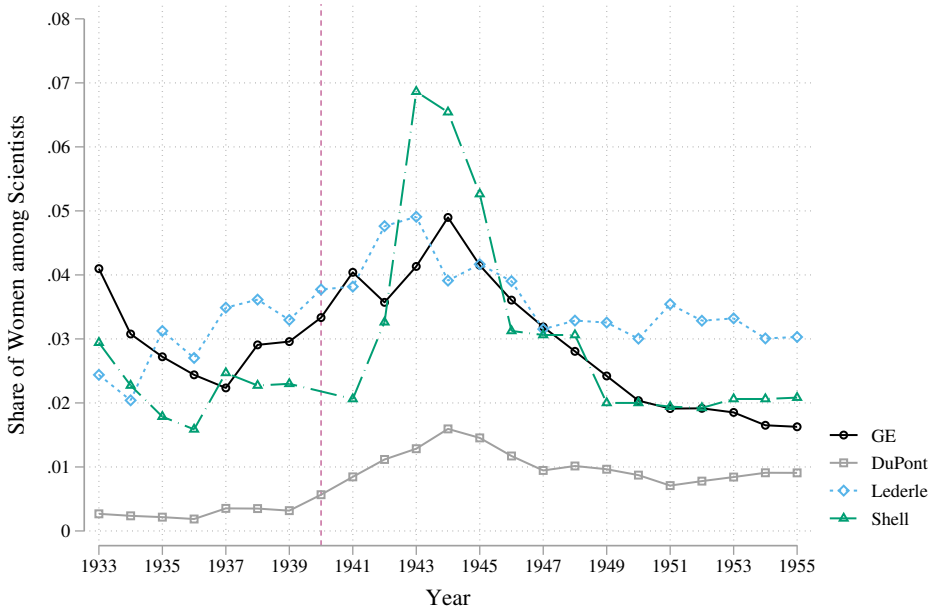
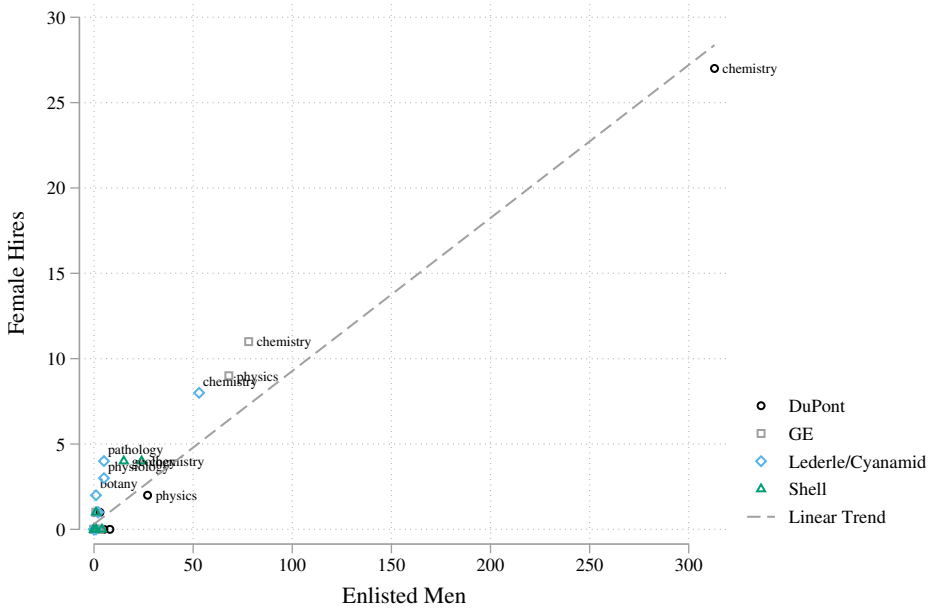


Figure 26: Enlistment and Female Entry a 4 Largest Employers



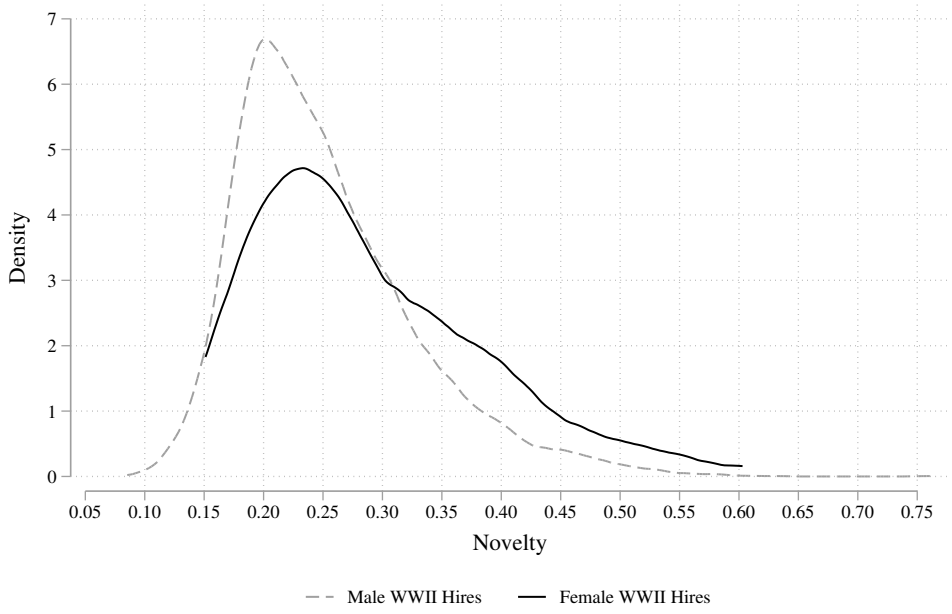
Note: Headcounts of female entry and enlisted male scientists at research teams at DuPont, GE, Lederle/American Cyanamid, and Shell. Teams are defined as groups of scientists employed at the same firm and working in the same discipline.

Figure 27: Event Study: Enlistment and Female Entry a 4 Largest Employers



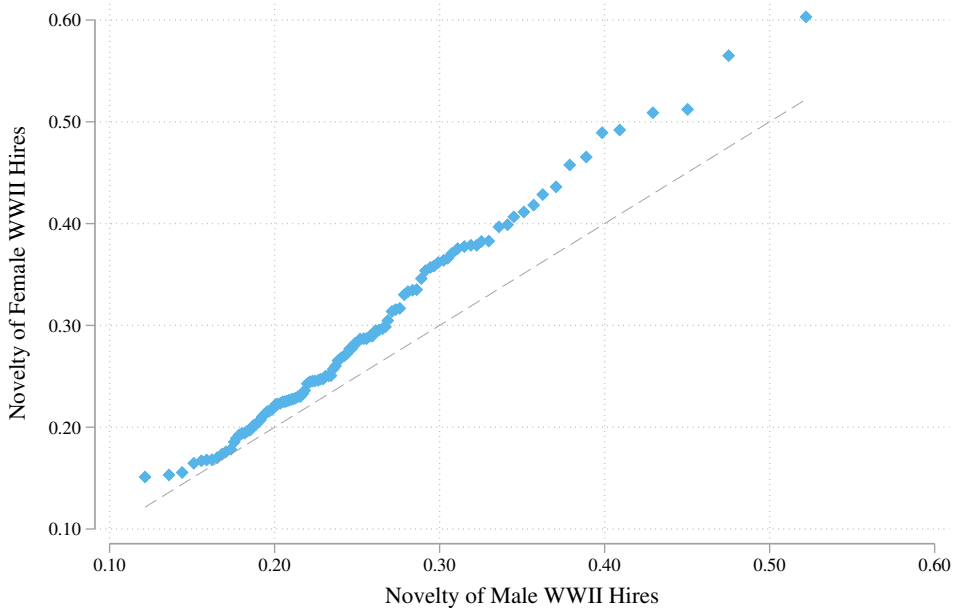
Note: Event study for female entry into research teams at DuPont, GE, Lederle/American Cyanamid, and Shell that were differentially exposed to enlistment during WWII.

Figure 28: Novelty



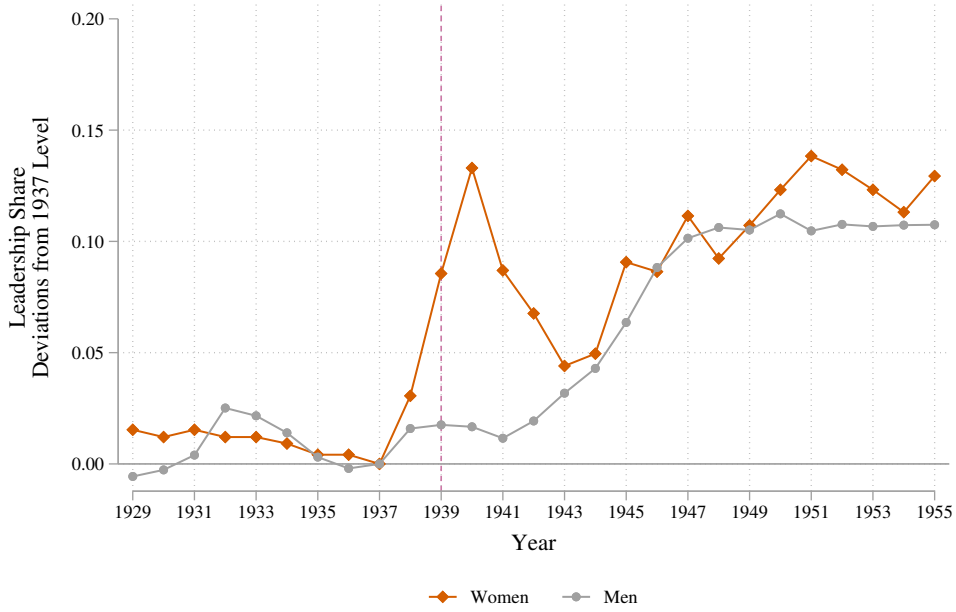
Note: Novelty of male and female entrants relative to incumbent scientists at their WWII employer.

Figure 29: Novelty Quantile-Quantile Plot



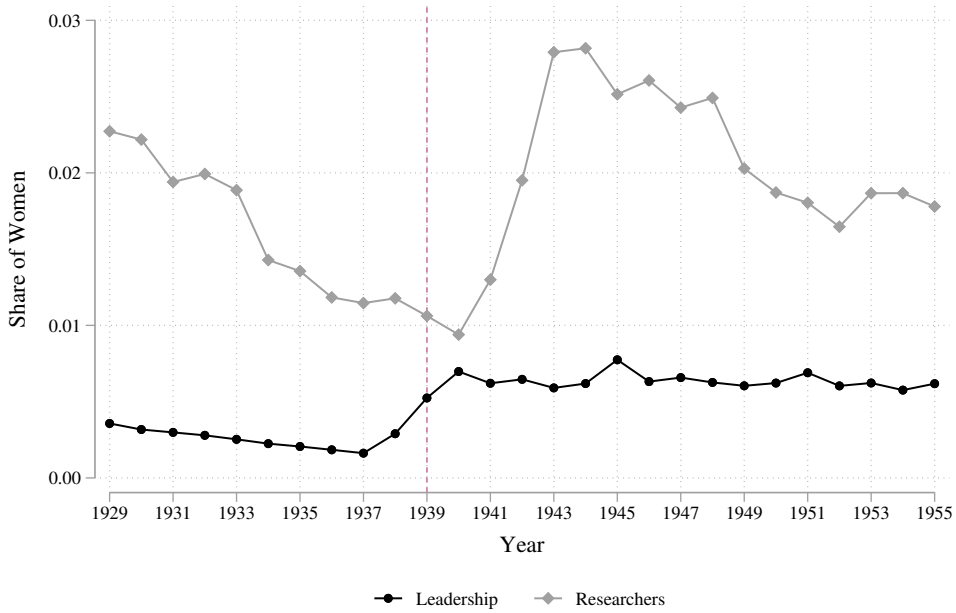
Note: Novelty of male and female entrants relative to incumbent scientists at their WWII employer at each quantile.

Figure 30: Gender Gap in Leadership Roles



Note: Share of male and female scientists in leadership roles at US firms. Differenced with 1937 level for each series.

Figure 31: Share of Women in Research and Leadership Roles



Note: Share of female scientists in research and leadership roles at US firms.

Figure 32: Female Scientists' Job Titles at 4 Largest Employers

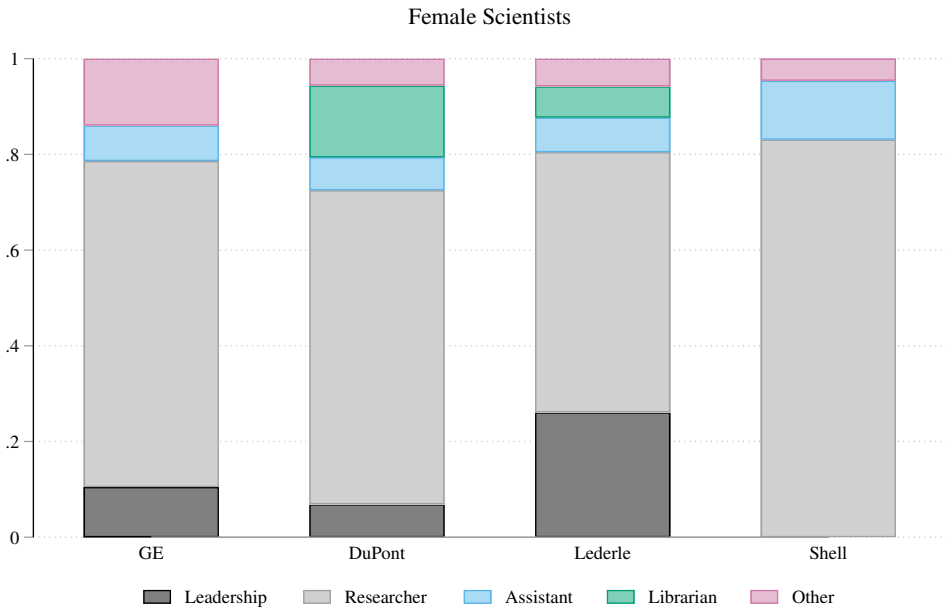
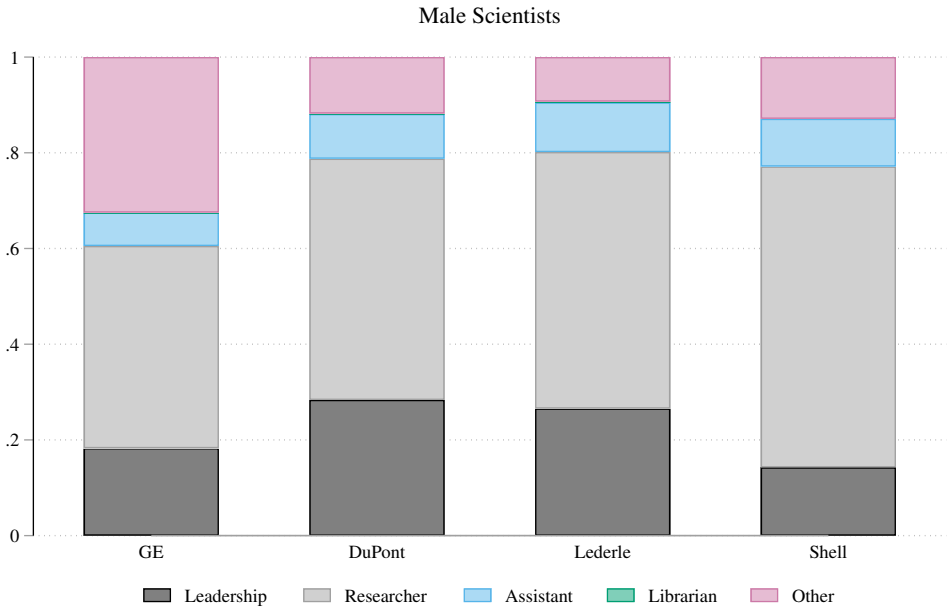


Figure 33: Male Scientists' Job Titles at 4 Largest Employers



7. TABLES

Table 1: Balance Table: Firm Traits in 1939

	Full sample			Split by 1+ Scientists Enlisting in WWII (1/0)			
Trait	Mean	SD	N	Mean (0)	Mean (1)	Diff (1–0)	p
Employed Scientists	7.459	31.941	473	1.881	12.268	10.386	0.0004
Female Scientists	0.076	0.394	473	0.018	0.126	0.108	0.0029
Female Share	0.012	0.094	473	0.014	0.010	-0.003	0.7093
Female Hires	0.013	0.112	473	0.005	0.020	0.015	0.1435
Male Hires	0.981	3.673	473	0.132	1.713	1.580	0.0000
Scientists' Avg. Age	35.079	7.766	473	36.946	33.470	-3.476	0.0000
Publications / Scientist	0.229	0.509	473	0.238	0.222	-0.016	0.7291
Patents / Scientist	0.222	0.817	473	0.205	0.236	0.031	0.6814
Share Enlisted Scientists	0.101	0.129	471	0.000	0.187	0.187	0.0000
				Split by Hiring 1+ Women during WWII (1/0)			
Trait				Mean (0)	Mean (1)	Diff (1–0)	p
Employed Scientists				3.983	34.426	30.443	0.0000
Female Scientists				0.036	0.389	0.353	0.0000
Female Share				0.012	0.014	0.002	0.8766
Female Hires				0.012	0.019	0.007	0.6848
Male Hires				0.542	4.389	3.847	0.0000
Scientists' Avg. Age				35.241	33.825	-1.416	0.2078
Publications / Scientist				0.229	0.231	0.001	0.9861
Patents / Scientist				0.214	0.288	0.074	0.5306
Share Enlisted Scientists				0.097	0.131	0.035	0.0639

Balance table for firm traits in 1939. Means and standard deviations (SD) for 473 firms that employ at least one scientist in 1939. P-values from two-sided t-tests with equal variances that compare means between firms that are exposed to enlistment and other firms (top panel) and firms that hire women during WWII and other firms (bottom panel).

Table 2: Firm-Level TWFE Estimates of Enlistment on Female Entry and Exit

Y =	(1) 1[Enlisted]	(2) 1[Enlisted]	(3) 1[Enlisted]
1[Industry Employment]	-0.004		
	(0.003)		
1[Prewar Pubs.]		-0.001	
		(0.005)	
1[Prewar Pats.]			-0.009**
			(0.004)
Model	OLS	OLS	OLS
Mean Y	0.147	0.141	0.141
Observations	70,033	13,862	13,862

Note: OLS predictions of individual scientists' enlistment. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 3: Firm-Level TWFE Estimates of Enlistment on Female Entry and Exit

	(1) Female Entry	(2) Female Exit	(3) Female Entry	Female Exit
Enlistment (1/0)	0.020***	0.014***		
	(0.006)	(0.004)		
Enlistment (%)			0.010**	0.005
			(0.004)	(0.004)
Model	OLS	OLS	OLS	OLS
Year FE	✓	✓	✓	✓
Field FE	✓	✓	✓	✓
Mean Y	0.011	0.007	0.011	0.008
Observations	19,711	19,711	17,885	17,885

Note: OLS estimates of two-way fixed effects difference-in-differences specifications. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 4: Robustness: Excluding Scientists who Volunteered

Y =	(1) Female Entry	(2) Female Entry	(3) Publications per Scientist	(4) Publications per Scientist	(5) Patents per Scientist	(6) Patents per Scientist
	DiD		IV		IV	
Enlistment	0.020***		0.418***		0.066	
	(0.006)		(0.147)		(0.220)	
Draft		0.025***		0.321**		0.065
		(0.007)		(0.132)		(0.208)
Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Mean Y	0.011	0.011	0.152	0.152	0.105	0.105
Observations	19,711	19,711	19,711	19,711	19,711	19,711
Cragg-Donald F			1101.905	1275.110	1101.905	1275.110
Kleibergen-Paap F			37.500	34.345	37.500	34.345

OLS DiD estimates and IV estimates that define treatment as enlistment (Columns 1, 3, 5) and draft (Columns 2, 4, 6). *** p < 0.01 ** p < 0.05 * p < 0.1

Table 5: Robustness: DiD with Staggered Exposure

	(1) Female Entry	(2) Female Entry	(3) Female Entry	(4) Female Entry
Draft Exposure		0.031***		0.033***
		(0.011)		(0.012)
Enlistment Exposure	0.032***		0.034***	
	(0.010)		(0.010)	
Model	TWFE	TWFE	ETWFE	ETWFE
Effects Assumption	homog.	homog.	heterog.	heterog.
Control Group	All	All	Never Treated	Never Treated
Year FE	✓	✓	✓	✓
Field FE	✓	✓	✓	✓
Mean Y	0.011	0.011	0.011	0.011
Observations	17,997	17,997	17,997	17,997

Note: OLS TWFE DiD estimates. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 6: Firm-Level TWFE Estimates of Female Entry on Productivity

	(1) Publications/ Scientist	(2) Publications/ Scientist	(3) Publications/ Scientist	(4) Patents/ Scientist	(5) Patents/ Scientist	(6) Patents/ Scientist
Female Hires	0.090***	0.114***	0.069***	-0.016	-0.009	0.104
$\times$ t $\geq$ 1940	(0.026)	(0.036)	(0.023)	(0.044)	(0.049)	(0.106)
Sample	All Scientists	Excl. WWII	Incumbents	All Scientists	Excl. WWII	Incumbents
Year FE	✓	✓	✓	✓	✓	✓
Field FE	✓	✓	✓	✓	✓	✓
Mean Y	0.152	0.163	0.125	0.105	0.105	0.099
Observations	19,711	13,712	19,688	19,711	13,712	19,688

Note: OLS estimates of two-way fixed effects difference-in-differences specifications. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 7: Controlling for the Size of Research Teams - TWFE Publications

	(1) Publications / Scientist	(2) Publications / Scientist	(3) Publications / Scientist	(4) Publications / Scientist
Hired Women (1/0)	0.089***	0.078***	0.079***	0.096***
	(0.026)	(0.028)	(0.028)	(0.027)
N Scientists		0.000	0.000	0.002*
		(0.000)	(0.000)	(0.001)
Δ N Scientists			0.001	0.001
			(0.001)	(0.002)
N Scientists $\times$ WWII				-0.001*
				(0.001)
Δ N Scientists $\times$ WWII				-0.000
				(0.002)
Model	OLS	OLS	OLS	OLS
Year FE	✓	✓	✓	✓
Field FE	✓	✓	✓	✓
Mean Y	0.153	0.153	0.153	0.153
Observations	17,997	17,997	17,997	17,997

Note: OLS estimates of two-way fixed effects difference-in-differences specifications. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 8: Controlling for the Size of Research Teams - TWFE Patents

	(1) Patents / Scientist	(2) Patents / Scientist	(3) Patents / Scientist	(4) Patents / Scientist
Hired Women (1/0)	-0.018	-0.019	-0.019	-0.009
	(0.043)	(0.044)	(0.044)	(0.046)
N Scientists		0.000	0.000	0.002
		(0.000)	(0.000)	(0.001)
Δ N Scientists			0.000	-0.007*
			(0.001)	(0.004)
N Scientists × WWII				-0.002*
				(0.001)
Δ N Scientists × WWII				0.008*
				(0.004)
Model	OLS	OLS	OLS	OLS
Year FE	✓	✓	✓	✓
Field FE	✓	✓	✓	✓
Mean Y	0.106	0.106	0.106	0.106
Observations	17,997	17,997	17,997	17,997

Note: OLS estimates of two-way fixed effects difference-in-differences specifications. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 9: Controlling for the Age Composition of Research Teams - TWFE Publications

	(1) Publications per Scientist	(2) Publications per Scientist	(3) Publications per Scientist	(4) Publications per Scientist
Hired Women (1/0)	0.089***	0.087***	0.087***	0.082***
	(0.026)	(0.027)	(0.027)	(0.026)
Mean Age		-0.001	-0.003	-0.011
		(0.001)	(0.005)	(0.010)
Mean Age Sq.			0.000	0.000
			(0.000)	(0.000)
Mean Age × WWII				0.002
				(0.011)
Mean Age Sq. × WWII				-0.000
				(0.000)
Model	OLS	OLS	OLS	OLS
Year FE	✓	✓	✓	✓
Field FE	✓	✓	✓	✓
Mean Y	0.153	0.153	0.153	0.153
Observations	17,997	17,997	17,997	17,997

Note: OLS estimates of two-way fixed effects difference-in-differences specifications. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 10: Controlling for the Age Composition of Research Teams - TWFE Patents

	(1) Patents per Scientist	(2) Patents per Scientist	(3) Patents per Scientist	(4) Patents per Scientist
Hired Women (1/0)	-0.018	-0.007	-0.008	-0.011
	(0.043)	(0.043)	(0.043)	(0.042)
Mean Age		0.006***	0.017***	0.025
		(0.002)	(0.005)	(0.016)
Mean Age Sq.			-0.000**	-0.000
			(0.000)	(0.000)
Mean Age × WWII				-0.016
				(0.018)
Mean Age Sq. × WWII				0.000
				(0.000)
Model	OLS	OLS	OLS	OLS
Year FE	✓	✓	✓	✓
Field FE	✓	✓	✓	✓
Mean Y	0.106	0.106	0.106	0.106
Observations	17,997	17,997	17,997	17,997

Note: OLS estimates of two-way fixed effects difference-in-differences specifications. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 11: Firm-Level TSLS Estimates of the Effects of Female Entry in Publications

Y =	(1) Productivity	(2) Productivity	(3) Hired Women (1/0)	(4) Productivity
	OLS	Reduced Form	First Stage	IV
Hired Women (1/0)	0.090***			0.418***
	(0.026)			(0.147)
Enlistment (1/0)		0.052***	0.125***	
		(0.017)	(0.020)	
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Mean Y	0.152	0.152	0.054	0.152
Observations	19,711	19,711	19,711	19,711
Cragg-Donald F				1101.905
Kleibergen-Paap F				37.500

Note: Two-stage least squares IV estimates. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 12: Firm-Level TSLS Estimates of the Effects of Female Entry on Patents

Y =	(1) Productivity	(2) Productivity	(3) Hired Women (1/0)	(4) Productivity
	OLS	Reduced Form	First Stage	IV
Hired Women (1/0)	-0.016			0.066
	(0.044)			(0.220)
Enlistment (1/0)		0.008	0.125***	
		(0.027)	(0.020)	
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Mean Y	0.105	0.105	0.054	0.105
Observations	19,711	19,711	19,711	19,711
Cragg-Donald F				1101.905
Kleibergen-Paap F				37.500

Note: Two-stage least squares IV estimates. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 13: Firm-Level TSLS Estimates: Productivity Effects of Female Entry on Incumbent Scientists

Y =	(1) Incumbents' Productivity	(2) Incumbents' Productivity	(3) Incumbents' Productivity	(4) Incumbents' Productivity
	Reduced Form	IV	Reduced Form	IV
Hired Women (1/0)		0.322**		0.295
		(0.159)		(0.256)
Enlistment (1/0)	0.040**		0.037	
	(0.020)		(0.032)	
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Mean Y	0.128	0.128	0.099	0.099
Observations	19,711	19,711	19,711	19,711
Cragg-Donald F		1101.905		1101.905
Kleibergen-Paap F		37.500		37.500

Note: Two-stage least squares IV estimates. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 14: Controlling for the Size of Research Teams - IV Publications

Y =	(1) Publications / Scientist	(2) Publications / Scientist	(3) Publications / Scientist	(4) Publications / Scientist
	IV	IV	IV	IV
Hired Women (1/0)	0.418***	0.440***	0.442***	0.520***
	(0.147)	(0.167)	(0.168)	(0.189)
N Scientists		-0.000	-0.000	0.003*
		(0.000)	(0.000)	(0.002)
Δ N Scientists			0.002	0.007
			(0.001)	(0.004)
N Scientists× WWII				-0.002*
				(0.001)
Δ N Scientists × WWII				-0.006
				(0.004)
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Mean Y	0.152	0.152	0.152	0.152
Observations	19,711	19,711	19,711	19,711
Cragg-Donald F	1101.905	888.593	887.319	769.904
Kleibergen-Paap F	37.500	30.724	30.664	25.769

Note: TSLS IV estimates. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 15: Controlling for the Size of Research Teams - IV Patents

Y =	(1) Patents per Scientist	(2) Patents per Scientist	(3) Patents per Scientist	(4) Patents per Scientist
	IV	IV	IV	IV
Hired Women (1/0)	0.066	0.079	0.079	0.109
	(0.220)	(0.252)	(0.252)	(0.275)
Firm Size		-0.000	-0.000	0.002
		(0.001)	(0.001)	(0.002)
Δ Firm Size			0.000	-0.006
			(0.001)	(0.005)
Firm Size × WWII				-0.002
				(0.001)
Δ Firm Size × WWII				0.006
				(0.005)
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Mean Y	0.105	0.105	0.105	0.105
Observations	19,711	19,711	19,711	19,711
Cragg-Donald F	1101.905	888.593	887.319	769.904
Kleibergen-Paap F	37.500	30.724	30.664	25.769

Note: TSLS IV estimates. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 16: Controlling for the Age Composition of Research Teams - IV Publications

Y =	(1) Publications / Scientist	(2) Publications / Scientist	(3) Publications / Scientist	(4) Publications / Scientist
	IV	IV	IV	IV
Hired Women (1/0)	0.418***	0.440***	0.442***	0.520***
	(0.147)	(0.167)	(0.168)	(0.189)
N Scientists		-0.000	-0.000	0.003*
		(0.000)	(0.000)	(0.002)
Δ N Scientists			0.002	0.007
			(0.001)	(0.004)
N Scientists× WWII				-0.002*
				(0.001)
Δ N Scientists × WWII				-0.006
				(0.004)
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Mean Y	0.152	0.152	0.152	0.152
Observations	19,711	19,711	19,711	19,711
Cragg-Donald F	1101.905	888.593	887.319	769.904
Kleibergen-Paap F	37.500	30.724	30.664	25.769

Note: TSLS IV estimates. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 17: Controlling for the Age Composition of Research Teams - IV Publications

Y =	(1) Patents per Scientist	(2) Patents per Scientist	(3) Patents per Scientist	(4) Patents per Scientist
	IV	IV	IV	IV
Hired Women (1/0)	0.066	0.079	0.079	0.109
	(0.220)	(0.252)	(0.252)	(0.275)
Firm Size		-0.000	-0.000	0.002
		(0.001)	(0.001)	(0.002)
Δ Firm Size			0.000	-0.006
			(0.001)	(0.005)
Firm Size × WWII				-0.002
				(0.001)
Δ Firm Size × WWII				0.006
				(0.005)
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Mean Y	0.105	0.105	0.105	0.105
Observations	19,711	19,711	19,711	19,711
Cragg-Donald F	1101.905	888.593	887.319	769.904
Kleibergen-Paap F	37.500	30.724	30.664	25.769

Note: TSLS IV estimates. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 18: Largest Employers of Female Scientists

Firm	Size	Enlisted Men	Enlisted Men / Size	Female Hires	Female Hires / Enlisted Men
DuPont	2,338	363	15.7%	30	8.3%
GE	1,110	156	14.3%	22	14.1%
Lederle/Cyanamid	512	69	14.0%	19	27.5%
Shell	327	45	14.2%	10	22.2%

Note: Scientific personnel at the 4 largest employers of female scientists.

Table 19: Pooled IV Estimates for Publications at the Level of Research Teams

Y =	(1) Publications/ Scientist	(2) Publications/ Scientist	(3) Hired Women (1/0)	(4) Publications/ Scientist
	OLS	Reduced Form	First Stage	IV
Hired Women (1/0)	0.023			0.230**
	(0.053)			(0.098)
Enlistment (1/0)		0.092*	0.400***	
		(0.053)	(0.031)	
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Mean Y	0.182	0.182	0.199	0.182
Observations	966	966	966	966
Cragg-Donald F				171.619
Kleibergen-Paap F				248.981

Note: Two-stage least squares IV estimates at the level of research teams. Research teams are defined as scientists who work at the same firm, in the same discipline, at the same time. Pooled specification for research teams at DuPont, GE, Lederle/American Cyanamid, and Shell. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 20: Pooled IV Estimates for Patents at the Level of Research Teams

Y =	(1) Patents/ Scientist	(2) Patents/ Scientist	(3) Hired Women (1/0)	(4) Patents/ Scientist
	OLS	Reduced Form	First Stage	IV
Hired Women (1/0)	0.036			-0.011
	(0.029)			(0.083)
Enlistment (1/0)		-0.004	0.400***	
		(0.029)	(0.031)	
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Mean Y	0.064	0.064	0.199	0.064
Observations	966	966	966	966
Cragg-Donald F				171.619
Kleibergen-Paap F				248.981

Note: Two-stage least squares IV estimates at the level of research teams. Research teams are defined as scientists who work at the same firm, in the same discipline, at the same time. Pooled specification for research teams at DuPont, GE, Lederle/American Cyanamid, and Shell. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 21: Separate IV Estimates for Publications at the Level of Research Teams

Y =	(1) Publications/ Scientist	(2) Publications/ Scientist	(3) Publications/ Scientist	(4) Publications/ Scientist	(5) Publications/ Scientist
	All 4 Firms	DuPont	GE	Lederle/ Cyanamid	Shell
Hired	0.230**	-0.012	0.346	0.323***	0.260**
Women	(0.098)	(0.245)	(0.351)	(0.106)	(0.113)
Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Mean Y	0.182	0.163	0.175	0.243	0.137
Observations	966	276	299	230	161
Cragg-Donald F	171.619	30.125	23.121	78.800	56.143
Kleibergen-Paap F	248.981	52.446	30.189	106.700	81.451

Note: Two-stage least squares IV estimates. Enlistment as IV for female entry. Within firm estimates compare research teams at the same firm with differential enlistment exposure. Research teams are defined as scientists who work at the same firm, in the same discipline, at the same time. *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table 22: Separate IV Estimates for Patents at the Level of Research Teams

Y =	(1) Patents/ Scientist	(2) Patents/ Scientist	(3) Patents/ Scientist	(4) Patents/ Scientist	(5) Patents/ Scientist
	All 4 Firms	DuPont	GE	Lederle/ Cyanamid	Shell
Hired	-0.011	-0.474**	0.166	0.171***	0.073
Women	(0.083)	(0.209)	(0.307)	(0.033)	(0.108)
Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Mean Y	0.064	0.077	0.056	0.067	0.051
Observations	966	276	299	230	161
Cragg-Donald F	171.619	30.125	23.121	78.800	56.143
Kleibergen-Paap F	248.981	52.446	30.189	106.700	81.451

Note: Two-stage least squares IV estimates. Enlistment as IV for female entry. Within firm estimates compare research teams at the same firm with differential enlistment exposure. Research teams are defined as scientists who work at the same firm, in the same discipline, at the same time. *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$

Table 23: Novelty: WWII Hires' Average Distance to Incumbent Scientists

	(1) Novelty	(2) Novelty	(3) Novelty	(4) Novelty
Female	0.034***	0.029***	0.028***	0.015**
	(0.010)	(0.007)	(0.007)	(0.007)
Sample	WWII Hires	WWII Hires	WWII Hires	WWII Hires
Model	OLS	OLS	OLS	OLS
Firm FE		✓	✓	✓
Year of Birth FE			✓	✓
Volume FE				✓
Mean Y	0.253	0.253	0.253	0.253
Observations	4,610	4,610	4,610	4,610
R-squared	0.005	0.300	0.313	0.428

OLS estimates for WWII hires (1940-46) compared with incumbent scientists (1935-39) at their WWII employer. Novelty calculated as 1 minus the average cosine similarity between the average embeddings of incumbent scientists and WWII entrants at firm level. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 24: Novelty: WWII Hires' Distance to Average Incumbent Scientists

	(1) Novelty	(2) Novelty	(3) Novelty	(4) Novelty
Female	0.027***	0.032***	0.031***	0.015**
	(0.009)	(0.008)	(0.008)	(0.008)
Sample	WWII Hires	WWII Hires	WWII Hires	WWII Hires
Model	OLS	OLS	OLS	OLS
Firm FE		✓	✓	✓
Year of Birth FE			✓	✓
Field FE				✓
Mean Y	0.159	0.159	0.159	0.159
Observations	4,809	4,809	4,809	4,809
R-squared	0.002	0.331	0.343	0.461

OLS estimates for WWII hires (1940-46) compared with incumbent scientists (1935-39) at their WWII employer. Novelty calculated as 1 minus the cosine similarity between the word embeddings of the centroid of incumbent scientists and WWII entrants at firm level. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 25: Collaborations for Male Scientists

Y =	(1) Publications	(2) Publications by Male Scientists	(3) Publications by Male Scientists with Female Co-Authors	(4) Publications by Male Scientists with Co-Workers	(5) Publications by Male Scientists with Female Co-Workers
Hired	0.090***	0.097***	0.001	0.021***	0.000*
Women	(0.026)	(0.026)	(0.002)	(0.007)	(0.000)
Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Mean Y	0.152	0.153	0.001	0.007	0.000
Observations	19,711	19,711	19,711	19,711	19,711
Firms	857	857	857	857	857
R2	0.330	0.328	0.174	0.155	0.224

Note: OLS estimates of two-way fixed effect difference-in-differences specifications. Co-workers are defined as scientists who work at the same firm i the same year. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 26: Productivity of Male Scientists Working with Women as Assistants, Researchers, and Managers

Y =	(1) Publications	(2) Publications by Male Scientists	(3) Publications by Male Scientists with Female Co-Authors	(4) Publications by Male Scientists with Co-Workers	(5) Publications by Male Scientists with Female Co-Workers
Women as	-0.053	-0.062	0.000	-0.005**	-0.000
Assistants	(0.049)	(0.046)	(0.001)	(0.002)	(0.000)
Women as	0.110***	0.121***	0.001	0.025***	0.000
Researchers	(0.031)	(0.032)	(0.001)	(0.008)	(0.000)
Women as	0.037	0.039	-0.007	0.019	0.001
Leadership	(0.050)	(0.050)	(0.008)	(0.014)	(0.001)
Year FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Mean Y	0.152	0.153	0.001	0.007	0.000
Observations	19,711	19,711	19,711	19,711	19,711
Firms	857	857	857	857	857
R2	0.331	0.329	0.174	0.155	0.225

Note: Variables denote highest level at which female scientists are employed at a male scientist's employer. OLS estimates of two-way fixed effect difference-in-differences specifications. Co-workers are defined as scientists who work at the same firm i the same year. *** p < 0.01 ** p < 0.05 * p < 0.1

Table 27: Gender Gap in Promotions

Y =	(1) Promotion (t+1)	(2) Promotion (t+1)	(3) Promotion (t+1)	(4) Promotion (t+1)	(5) Promotion (t+1)	(6) Promotion (t+1)
Female	-0.014***	-0.014***	-0.013***	-0.011***	-0.010**	-0.009**
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Patents (t)		0.008***	0.006***	0.007***	0.006**	0.006**
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Publications (t)		0.003	0.002	0.002	0.003*	0.003
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Years in Job			0.002***	0.002***	0.002***	0.002***
			(0.001)	(0.001)	(0.001)	(0.001)
Years in Job^2			-0.000***	-0.000***	-0.000***	-0.000***
			(0.000)	(0.000)	(0.000)	(0.000)
Birth Year FE				✓	✓	✓
Firm FE					✓	✓
Volume FE						✓
Mean Y	0.025	0.025	0.025	0.025	0.025	0.025
Observations	36,835	36,835	36,835	36,835	36,835	36,835
Scientists	6,029	6,029	6,029	6,029	6,029	6,029

Note: OLS estimates. Sample restricted to scientists who work in the same firm for at least two consecutive years. Outcome variable defined as indicator for scientists in a leadership role if they were in a research role the year before at the same firm. *** p < 0.01 ** p < 0.05 * p < 0.1