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The Impact of Female Role Models on Female Individuals' Propensity to Study STEM in the US

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Abstract

Women are systematically underrepresented in science, technology, engineering and mathematics (STEM) bachelor's degree programs. Our paper contributes to previous research through studying the impact of the prevalence of female inventors on female individuals' propensity to pursue a STEM and math-intensive STEM bachelor's degree in the US. We use data from the IPUMS USA, United States Patent and Trademark Office (USPTO) and U.S. Bureau of Labor Statistics (BLS). Our empirical strategy exploits within-region and across-time changes in the share of female inventors and the female share of bachelor's degree holders who have studied STEM. A one-percentage point increase in the share of female inventors is associated with an increase of 0.296 percentage points and 0.295 percentage points in the probability that female bachelor's degree holders have studied STEM and math-intensive STEM, respectively, compared to their male counterparts. The marginal effect for a one-percentage point increase in the share of female inventors is correlated with a 0.040 percentage points and 0.098 percentage points increase in the probability for a female bachelor's degree holder to have studied STEM and math-intensive STEM, respectively. As a result, the increase in the share of female inventors in the recent decades could have contributed to the increase of the female share of STEM and math-intensive STEM bachelor's degree holders by 4.5% and 32.3%, respectively, between 1980 and 2008. Moreover, the results are robust to different specifications and falsification tests. An increase in the share of female inventors is not associated with an increase in various categories of non-STEM degrees, which strengthens the internal validity of this study, suggesting that role models likely affected female bachelor's degree holders' propensity to have studied STEM in the US.

Keywords: Education Economics, STEM, Bachelor's Degree, Female Inventors, Role Models

JEL: J16, I23, I24

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1 Introduction

Widespread gender gaps in education, income and labor markets persist globally (The Royal Swedish Academy of Sciences, 2023). Even though gender gaps are persisting, female employment rates are at an unprecedentedly high level globally. In the US, around 58% of the individuals who obtain a bachelor's degree are women, which implies that women are emerging as the better-educated gender (Goldin, 2024). However, women are systematically underrepresented in science, technology, engineering and mathematics (STEM). During the last decade, the female share in STEM has plateaued in almost all OECD countries. This is concerning as salaries are on average higher with smaller wage gap for STEM occupations. Hence, a closure of the gender gap within STEM could alleviate gender inequalities in labor markets (Breda et al., 2023).

Moreover, the plateauing trend is concerning since it likely represents a magnified talent loss, which could negatively impact the aggregate productivity (Breda et al., 2023). Various stakeholders in the private and public sector demand more STEM graduates. However, the supply of STEM students is too low to satisfy the demand. (Vooren et al., 2022). A closure of the gender gap in STEM and innovation is imperative to enhance economic growth and output. The Nobel laureates Romer and Nordhaus show that ideas-driven economic growth can be sustained over time (The Royal Swedish Academy of Sciences, 2018). Yet, fewer than 20 percent of all US patents list a woman as an inventor. A greater diversity between the genders within inventing and patenting could unlock a significant amount of innovation and economic growth, which propels the ideas-driven economic growth (Fechner & Shapanka, 2018).

There are individual-, contextual- and institutional-level factors for the persistence of the underrepresentation of women in STEM. Self-efficacy and sense of belonging are included in the individual-level factors and contextual-level factors include stereotypes, social class and family context. An institutional-level factor is lack of female role models within STEM (Evagorou et al., 2024). In STEM fields such as biology and medical sciences, the female participation rate has increased, while in math-intensive STEM fields, such as physics, mathematics and computer science, women are particularly underrepresented. Women obtained only 21% of the bachelor's degrees in computer science, 23% in engineering while receiving 51% of the degrees in chemistry. There is therefore interest in reducing the persistent gender gap and addressing the underrepresentation of women in math-intensive STEM fields (Luo et al., 2022).

Our paper contributes to the existing literature through evaluating the mechanism in which role models affect female bachelor's degree holders' propensity to graduate with a STEM bachelor's degree. We use female inventors as a proxy for role models. In addition to investigating the relationship between female inventors and the propensity for a female bachelor's degree holder to have studied STEM, the propensity for female bachelor's degree holders to have studied math-intensive STEM is evaluated. More specifically, this thesis studies the following research question:

- How does the share of female inventors impact the propensity of female bachelor's degree holders to have studied overall STEM and math-intensive STEM in the US?

The findings would be relevant for stakeholders such as policymakers to understand how much female inventors have contributed to the increase of females in STEM studies. The issue is relevant for policymakers as it evaluates whether higher exposure to female inventors could increase the female share in STEM studies. In turn, the stakeholders could draw conclusions on how to further address the systematic gender gap. These conclusions could be whether the exposure to female inventors should be increased or if there are other channels that could be more effective in increasing women's representation in STEM.

To study the research question, we retrieved cross-sectional data from the IPUMS USA. From IPUMS USA, we collected two datasets: the first dataset consists of data from American Community Surveys (ACS) between 2009 and 2024 and include the individuals' degreefield, gender, birthyear, birthplace and sample weight; the second dataset from IPUMS USA consists of data from the ACS and decennial censuses and includes the state-level control variables female college attendance rate and the female labor force participation rate for years 1980, 1990 and between 2000 and 2008. The unemployment rate for the years 1980 and 2008 was collected from the U.S. Bureau of Labor Statistics (BLS). Moreover, the data for patents, which is used as a proxy for inventors, i.e. potential role models, was collected from the United States Patent and Trademark Office (USPTO) to calculate the female share of inventors for patents granted between 1980 and 2008. The IPUMS datasets were filtered to include all US states and filtered by bachelor's degree holders. Afterwards, the data for the control variables and the share of female patents were matched to each individual in a given state and cohort. Our final dataset consists of the cohorts 1980, 1990 and between 2000 and 2008, the dependent variable whether a bachelor's degree holder has studied STEM and math-intensive STEM, respectively. It contains the independent variables gender and the female share of inventors in the cohort and state which the bachelor's degree holder belongs to and was born in. Moreover, the control variables and the sample weights are included.

Our methodology exploits within-region effects and across-time changes through a linear probability model (LPM). Our methodology consists of two regressions: the first evaluates how the share of female inventors impacts the propensity of a female bachelor's degree holders to have studied STEM, and the second math-intensive STEM. The differential effect is the coefficient to the interaction term "Share female inventors x Female", which measures the change in the likelihood of a female bachelor's degree holder to have studied STEM and math-intensive STEM, respectively, when the share of female inventors increases. The LPM includes control variables and state and cohort fixed effects and uses clustered robust errors. The control variables include the female labor force participation rate, female college attendance rate and unemployment rate in a given state and cohort. The regressions account for the sample weights as different individuals have different probabilities to be sampled by the IPUMS USA. The clustered robust errors are clustered at the state level and are used to control for the fact that the residual term is likely correlated among women within a state to ensure that the t-statistic is not overestimated, which would otherwise provide a more statistically significant estimate (Cameron & Miller, 2015).

Our results indicate that there was a positive and statistically significant correlation between a higher share of female inventors and higher probability of a female bachelor's degree holder to have studied both overall STEM and math-intensive STEM. In other words, a higher share of female inventors in the state where an individual grows up could contribute to closing the gender gap within STEM. A one-percentage point increase in share of female inventors is associated with a 0.296 percentage points and 0.295 percentage points increase in the probability for a female bachelor's degree holder to have studied STEM and math-intensive STEM, respectively, compared to their male counterparts. As for the marginal effect, a one-percentage point increase in the share of female inventors is correlated with an increase in the likelihood for a female bachelor's degree holder to have studied STEM by 0.040 percentage points and math-intensive STEM by 0.098 percentage points. Between the period 1980-2008, the share of female inventors increased by 6-percentage points. These results indicate that the increase in the share of female inventors in the recent decades could have contributed to increasing the female share in STEM by 4.5% and 32.3% in math-intensive STEM.

These results are robust to several different specifications and falsification tests. The falsification tests include testing whether an increase in the share of female inventors would impact the propensity for female students to have studied various categories of non-STEM degrees. Our results show that there is no correlation between an increase in the female share of inventors and the likelihood for a woman to have studied non-STEM degrees, which could strengthen the internal validity of this study. Another falsification test was to test whether an increase in the female share of medical patents could increase the propensity for female students to have studied math-intensive STEM. Since medical fields typically do not involve heavy mathematics, an increase in the female share of medical patents should not affect the propensity for female students to have studied math-intensive STEM. The results show a positive estimate which is statistically significant but is smaller in magnitude compared to the baseline results, which could indicate some sort of spillover effect.

Due to the lack of experimental and exogenous variation in our study, we cannot establish a causal relationship between the share of female inventors and propensity for a woman to have studied STEM. It is not plausible that we have included all confounding factors, and our results are likely biased due to omitted variables. Potential omitted variables include socioeconomic status (SES) and the industry composition of the state. Additionally, there were limitations with the data used, such as limited number of years which could be included. Further research could investigate other types of role models, such as female high school teachers and STEM workers. Besides, it could be interesting to evaluate this research question from a historical perspective using historical patents or in European countries.

The rest of the paper is organized as follows: Section 2 provides an overview of previous literature on the gender gap and role model. Section 3 documents the data we have used and Section 4 describes the methodology which has been employed. The results are presented in Section 5 and discussed in Section 6. Finally, we present our conclusions in Section 7.

2 Literature Review

In this section, we present an overview of previous research on the gender gap in STEM and the impact of role models. The first strand of literature explores the reasons for the persistent gender gap in STEM. The second strand examines how role models could impact women's choices in pursuing a STEM degree or career.

2.1 Reasons for the Gender Gap within STEM

There are three broad categories for the reasons for the lack of participation of women in STEM, namely individual-, contextual- and institutional-level factors. Individual-level factors, such as self-efficacy, sense of belonging, individual expectations for STEM academic success and gender identity present internal influences. These affect a person's behaviors and choices. A significant predictor for future interest in STEM and for the intake of students of all genders, is self-efficacy. However, in secondary education, female students have lower self-efficacy than male students even though female students' achievements are on average better than those of male students. Societal and cultural issues, family context, stereotypes and social class are examples of contextual-level factors. The sociocultural context affects the persistency of stereotypes in STEM fields. The school's culture, peer influence, role models, values, biases and the role and STEM competences of teachers are examples of institutional-level factors. Teaching practices can also reinforce stereotypes through stereotypical presentations (Evagorou et al., 2024). Also Vooren et al. (2022) describes a discrepancy in self-efficacy and self-confidence. Comparing women's self-confidence to men's in their ability for STEM, the reported self-confidence is on average lower for women. Lacking sense of belonging and self-confidence are common reasons for attrition from STEM programs.

Moreover, female and male students are viewed differently by parents, teachers and peers. There is a tendency of parents, teachers and peers to give less support for girls to pursue STEM, even when they have similar interests and capabilities as boys. Moreover, the belief in a girl's ability for mathematics and science from parents and teachers are lower and they do not perceive these subjects to be as important, nor do they expect as high performance from female students compared to male students (Luo et al., 2022). When investigating the impact of social agents, such as teachers or peers, on a female student to complete an undergraduate degree in STEM, Luo et al. (2022) categorize STEM in both general and math-intensive STEM fields. They found a positive association between STEM teachers as mentors and STEM but did not find an association between having a STEM teacher as mentor and female students completing a math-intensive STEM degree. Notably though, it was a STEM teacher as a mentor and not specifically a female STEM teacher. These factors explained by Luo et al. (2022) are examples relating to the contextual- and institutional-level factors from Evagorou et al. (2024), and show an example of how teachers and family can perpetuate stereotypes.

2.2 The Impact of Role Models

By observing role models' performances, students can increase their confidence in their ability, i.e. their self-efficacy. This is called observational learning. Not only can role models increase self-efficacy but also act as protection against the negative impact from stereotypes. To female students who are underrepresented within STEM, female role models are examples of women being able to succeed within STEM. A role model is most likely a person that the student identifies as relevant to or similar to themselves and generally considered to be selected by the student themselves. The role model cannot be assigned. Gender is an example of perceived similarity which choice of role model can be based on, however the role model can also be similar on a psychological level such as common interests, values or experiences such as discrimination (Lee et al., 2023).

A large number of papers have investigated the exposure to female role models both on a regular basis and on a one-off event. Carrell et al. (2010) finds that female role models can make a difference. They investigate the influence by the gender of professors at the United States Air Force Academy (USAFA) and show that it has a great effect on the performance in mathematics and science classes and the probability of choosing a STEM degree. The gender gap is even eliminated for STEM majors when female professors teach introductory mathematics and science classes for female students with high math skills. Also, Mansour et al. (2022) investigates the effects of female math and science professors in first-year courses at the USAFA, but how it impacts choice of occupation and post-graduate education. They find that being assigned a female professor increases the probability of a high-capability woman to work in STEM as well as obtaining a masters' degree in STEM. The effect of female professors on high-capability male students' likelihood of working or obtaining a master's degree in STEM was negative, however.

For high schools in North Carolina, the gender faculty composition influences how likely a female student is to declare and graduate with a STEM major. For female students with the highest math skills, the effects were the largest. The environment of an individual's pre-college years is in emerging evidence suggested to greatly impact their choice of major at college (Bottia et al., 2015). Breda et al. (2023) investigate what drives the success of a role model intervention at French high schools. The authors evaluate whether different role models are equally able to influence the decision of college degree through a one-hour intervention by female scientists. This brief exposure influenced the students' choice and perception of majors of undergraduate studies and reduced the occurrence of stereotypical views on a career in science and differences in perceived abilities based on gender. The most impactful interventions were those that improved the perceptions of careers within STEM, while at the same time not putting too much emphasis on the fact that women are underrepresented. They describe how there could be a self-fulfilling prophecy within STEM, as women are underrepresented in a traditionally male-dominated field. In other words, there are few opportunities for girls to engage with and be inspired by women working within STEM. A common notion is thus that female role models are more effective to inspire women of a career in STEM than men. According to Cheryan et al. (2011) women underestimate how they would perform in STEM. In contrast to Breda et al. (2023), Carrell et al. (2010) and Bottia et al. (2015), they find that the extent role models demonstrate STEM stereotypes could be more important for their belief of themselves succeeding in STEM than the role models' gender.

Several papers have investigated the effect of how role models influence the choice of education and whether female role models can increase the number of women who choose to study STEM. However, most investigate role models which are in close proximity to or in a close relationship to the students and who meet on a regular basis, such as mentors, teachers, professors or guest lecturers but, to the best of our knowledge, no other paper has investigated the impact of role models in the society, but with no close connection to the student, i.e. if the exposure to more female scientists in general can influence girls to study STEM as they could act as role models to improve e.g. self-efficacy for girls. Bell et al. (2019) investigates who becomes an inventor in the US and finds that girls who later become inventors are more likely to invent in a specific class of inventions if where they grew up had more women, but not men, who invented in that specific class. This is likely due to role models or network effects. Additionally, they find that the probability of becoming an inventor vary with characteristics at birth such as socioeconomic class and that moving to a high-innovation area as a child increases the likelihood of becoming an inventor, i.e. the likelihood of becoming an inventor is affected by a child's exposure to innovation during childhood, where the exposure can be either through the child's own family or neighborhood. Hence, this suggests that female inventors can act as role models and affect female students' choice of education and career. The findings of Olivetti et al. (2020) is further indicating that a woman's career decisions could be impacted by the women she is exposed to during her childhood years. More specifically, they find that there can be an impact on a young woman's labor supply by the mothers of her peers during her high school years. These mothers could impact the young woman's attitudes regarding motherhood and employment. The probability of a woman to work, particularly when she becomes a mother, increases if she was exposed to a greater share of mothers who are working during her adolescence.

We contribute to this previous strand of literature through evaluating how the share of female inventors could impact female students' choice of bachelor's degree programs. We build on the findings of Bell et al. (2019) that the field of workers in individuals' neighborhood during their childhood affects what they later do in their career and we use patents as a proxy for female inventors as role models. Most previous studies look at role models close to the students and are looking at interventions with relationships closer to the students. Meanwhile, we investigate another type of role model relationships. Additionally, Breda et al. (2023) is set in France and therefore it would be interesting to evaluate whether external role models, who high school students are exposed to, also have an impact in the US. Carrell et al. (2010) and Mansour et al. (2022) examine professors at the USAFA, which could have other results from our study, as students are selected to the USAFA. Bottia et al. (2015) is also investigating role models in the US, but for one specific state and for high school teachers as role models. Thus, no previous studies have, to our knowledge, evaluated how female inventors could affect female individuals' propensity to study STEM in the general American population.

3 Data

3.1 Datasets and Raw Data

To evaluate the effect of role models on inspiring female students to have studied STEM in bachelor's degree programs in the US, we have collected data from three sources: the IPUMS USA (originally, the "Integrated Public Use Microdata Series"), the United States Patent and Trademark Office (USPTO) and the U.S. Bureau of Labor Statistics (BLS). These datasets include data about the individuals' characteristics and patent data and control variables to isolate the effect female inventors have on the share of female students studying STEM and math-intensive STEM.

The IPUMS USA data consists of cross-sectional data for individuals with demographic, ethnic, educational and other personal characteristics sampled each census year. Two datasets were collected from IPUMS USA; the first consists of the American Community Survey (ACS) for census years between 2009 and 2024 and was used to identify whether a bachelor's degree holder have studied STEM and math-intensive STEM, in other words, constructing the dependent variable. The raw data being used include census year, sample weight, sex, birthyear, birthplace and degreefield. There was lacking data for degreefield in census years before 2009, since it was not asked for in the ACS. However, as this data was used retrospectively, which means that the dependent variable was constructed through identifying which degree an individual has attained, it is still possible to capture cohorts before 2009 as an individual who has graduated before 2009 could have been surveyed in the period 2009-2024. The second dataset uses the decennial census for years 1980, 1990 and 2000 and the ACSs for the years 2001 to 2008 to construct control variables. There were no censuses conducted for the years 1981 to 1989 nor 1991 to 1999. The raw data being retrieved include census year, sample weight, the state where the individual lived in, sex, education and labor force participation (Ruggles et al., 2025). This data is not used retrospectively but is used to construct control variables for the year of the respective survey as they control for the level of e.g. female labor force participation rate for the year of a given state and cohort.

The USPTO dataset included the raw data for the patents being granted each year. There was data for the number of women and men, who were granted patents, and the state they lived in. This dataset was used to calculate the share of female inventors in each state and for years between 1980-2008, which is the independent variable. The patent data from the USPTO dates back until 1976. However, we use the data for years 1980, 1990 and 2000 to 2008, since data for the control variables female labor force participation and female college attendance rate is only available for these years. The raw annualized data is cross-sectional and include grant year, the number of male inventors and female inventors as well as the WIPO technology fields classified by the World Intellectual Property Organization (USPTO, 2026; WIPO, n.d.). Moreover, the dataset from BLS was a panel data with the unemployment rate in each state and cohort year and was used as an additional control variable (BLS, 2026).

3.2 Descriptive and Summary Statistics

In the raw data from the first IPUMS dataset, there are 5641087 individual observations in total with 1973310 individuals who are bachelor's degree holders. There are 869640 men and 751851 women who have studied STEM, and 199627 men and 66982 women who have studied math-intensive STEM (Ruggles et al., 2025). The national average share of female inventors has increased from around 2.88% to 9.86% between 1980 to 2008, which implies that the share has more than tripled or a 6.98-percentage point increase (USPTO, 2026). The national average of female share of bachelor's degree holders with a STEM degree, by cohort, has increased from around 43.38% in 1980 to 49.58% in 2008, which corresponds an increase by 6.20 percentage points. As for the national average of female share of bachelor's degree holders who have studied math-intensive STEM, by cohort, the figure has increased from approximately 24.11% in 1980 to 26.23% in 2008, implying a 2.12-percentage point increase. Regarding the control variables, the unweighted state-level mean for unemployment rate has decreased from 6.8% to 5.3% from 1980 to 2008. The unweighted state-level mean for female labor force participation rate has increased from 50% in 1980 and to 61% in 2008 and the unweighted state-level mean for female college attendance rate has increased from around 31% to 46% from 1980 to 2008. More detailed tables about the descriptive summary statistics can be found in Appendix A3 (BLS, 2026; Ruggles et al., 2025).

3.3 Organizing and Cleaning Data

The first IPUMS dataset was filtered to include all US states and District of Columbia (DC) and filtered by bachelor's degree holders. The degreefield was encoded to a dummy variable for whether an individual has studied STEM and a math-intensive STEM program respectively. For example, the degreefields "Computer and Information Sciences", "Engineering Technologies" and "Mathematics and Statistics" were classified as math-intensive STEM, while "Medical and Health Sciences and Services" was classified as STEM but not math-intensive STEM; the full classifications of degreefield can be found in Table 9.2 in Appendix A2 (Homeland Security Investigations, 2024; Luo et al., 2022). Furthermore, several non-STEM degreefields have been classified into the three categories Business or Law, Linguistics, Culture or History, and Physical Fitness, Parks, Recreation, and Leisure for the robustness tests. More precisely, the category Linguistics, Culture or History, consists of the degreefields "Area, Ethnic, and Civilization Studies", "Linguistics and Foreign Languages", "English Language, Literature, and Composition", "Library Science", "Philosophy and Religious Studies", "Theology and Religious Vocations" and "History". As the number of women outnumber men in psychology graduate programs, we have chosen to not include psychology as a STEM degree to focus on the STEM degrees where women are systematically underrepresented (Fowler et al., 2018).

Moreover, outliers with respect to the share of women who have studied STEM and math-intensive STEM were filtered away based on the interquartile rule, meaning that observations smaller than the lower fence or larger than the upper fence were removed. The purpose of filtering away outliers is to mitigate the risk of there being extreme observations in the datasets biasing the estimate for our regressions. The lower fence and upper fence were calculated as Q1 – 1.5 * (Q3 – Q1) and Q3 + 1.5 * (Q3 – Q1) respectively where Q1 and Q3 are the observations in the 25th and 75th quartile respectively (Penn State Eberly College of Science, n.d.).

We assume that individuals graduate from high school and start college at the age of 18 across all cohorts. The cohorts were set to be equal to an individual's birth year plus 18, to measure the effect of exposure to female inventors for the year when female individuals graduate from high school. For example, an individual born in 1990 belongs to the cohort 2008. The decision to pursue a STEM degree is often made during high school (Luo et al., 2022). According to Zhao et al. (2026), the age of most first-year undergraduates at college is 17 or 18. In their study, the average age for the surveyed first-year students was 18. Additionally, a majority of high school graduates continue to college the same year as their high school graduation (BLS, 2024). Thus, we have assumed that the age at high school graduation is 18. Furthermore, two-thirds of 18-29 year olds have reported that they have never moved out of the state they were born in (Taylor et al., 2008). Therefore, we assume that the state of treatment is the state the individual was born in. After including the cohorts, the dataset was filtered by cohorts in the years 1980, 1990 and between 2000 and 2008.

The second IPUMS dataset was filtered to include all US states and DC. The control variables female labor force participation rate and female college attendance rate was calculated. Female labor force participation was calculated through taking the number of women who participated in the labor force including all individuals who are 16 years or older divided by the total number of women who are 16 years or older, in a given state and cohort (Ruggles et al., 2025). Female college attendance rate was calculated by dividing the number of women between 18 and 24 years old who have completed at least one year of college studies with the total number of women between ages 18 and 24, in a given state and cohort. The ages for female college attendance rate is in line with the method employed by Pew Research Center (2009) to calculate college enrollment rates. As for the patent data from the USPTO, the dataset was filtered to include all US states and DC. The share of female inventors was calculated through dividing the number of female inventors by the total number of inventors in a state and year. To account for the patent composition by sector, more specifically, to distinguish the patents based on whether they are patents related to the medical field, the data for the WIPO technology fields was used (WIPO, n.d.). The patents that were in the WIPO technology fields including “Medical technology”, “Pharmaceuticals”, “Biotechnology” and “Analysis of biological materials” were classified as medical patents and used in one of the robustness tests. The control variable for unemployment rate from the BLS dataset was directly matched to the individual’s cohort year and the state where the individual was born, i.e. the unemployment rate in 2008 is matched to individuals born in 1990 and thus belonging to cohort 2008. The data for the share of female patents and the control variables in a given state and cohort were matched to each bachelor’s degree holder in that state and cohort.

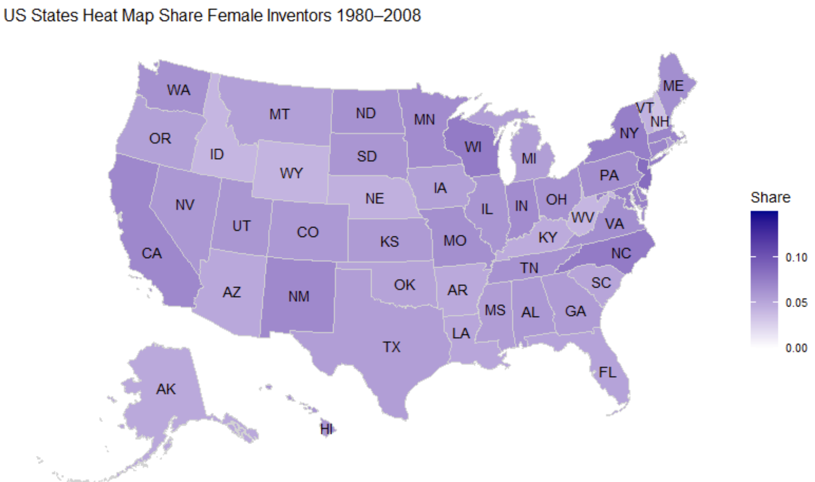
3.4 Final Data

The final dataset includes our dependent variable is whether a bachelor’s degree holder has a degree in STEM (regression 4.1) and math-intensive STEM (regression 4.2). The independent variables are the “Share of female inventors” and “Gender”. The control variables consist of the unemployment rate, the female college attendance rate and the female labor force participation rate. As data for the control variables female college attendance rate and female labor force participation rate calculated from IPUMS dataset was only available for 1980, 1990 and 2000 and onwards and the cutoff was set to cohorts until 2008, the final data set consists of cohorts 1980, 1990 and between 2000 and 2008. There are 1973310 individual observations who are bachelor’s degree holders in the raw data. After removing the outliers based on the interquartile rule, there are 1951617 observations in regression (4.1) and 1939389 in regression (4.2).

3.5 Heat Maps

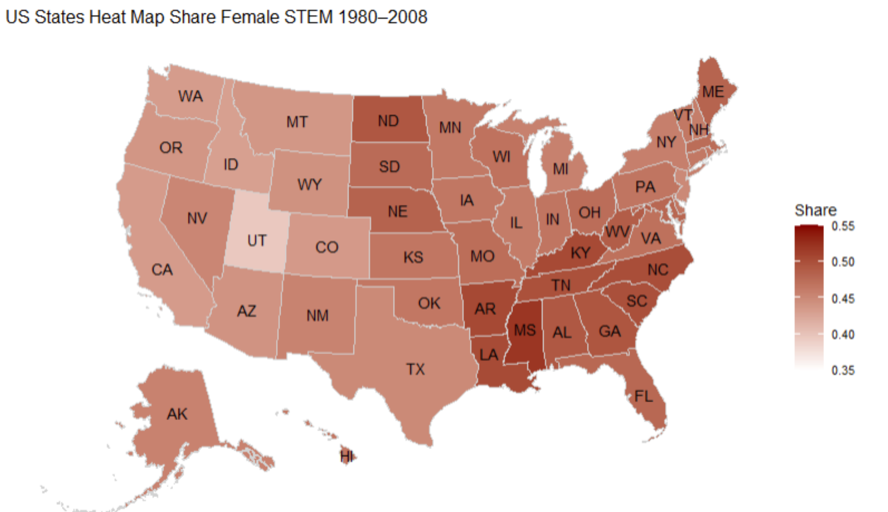
This section aims to visualize the variation between the states in the US through heat maps in the period between 1980 and 2008, with respect to the share of female inventors, the female share of bachelor's degree holders who have studied STEM and math-intensive STEM. Overall, an improvement in reducing the gender gaps could be observed (Figure 3-1-3.4). The shares for the heatmaps can be found in Tables 9.13-9.15 in Appendix A3 (Ruggles et al., 2025; USPTO, 2026).

Figure 3.1: Heat Map for share of female inventors between 1980-2008 in the US.



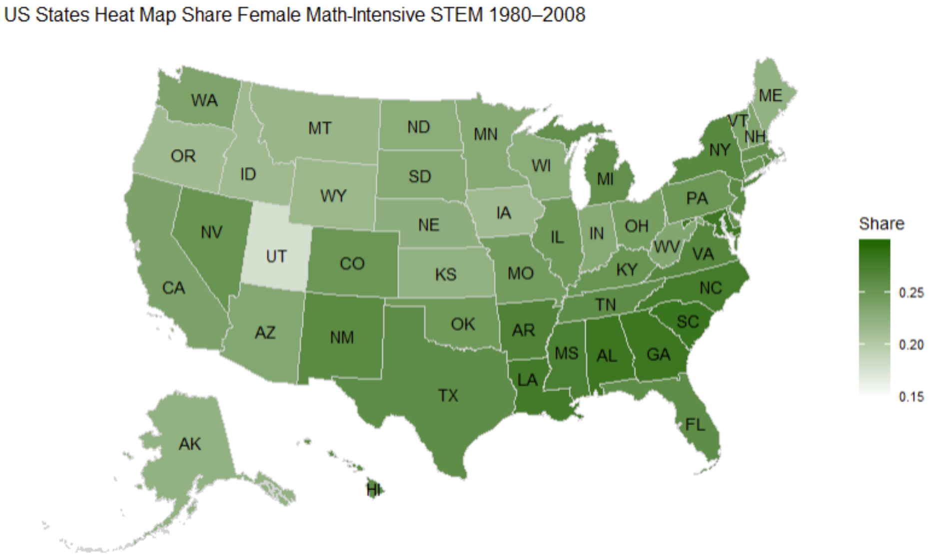
Note: Figure 3.1 summarizes the average share of female inventors between the years 1980 and 2008. The states with the highest shares are New Jersey (8.52%), District of Columbia (7.93%) and Wisconsin (7.66%) and the states with the lowest shares are New Hampshire (3.41%), Idaho (4.10%) and West Virginia (4.10%). Source: Authors' rendering of USPTO data (2026).

Figure 3.2: Heat Map for the female share of bachelor's degree holders who have studied STEM for cohorts between 1980-2008 in the US.



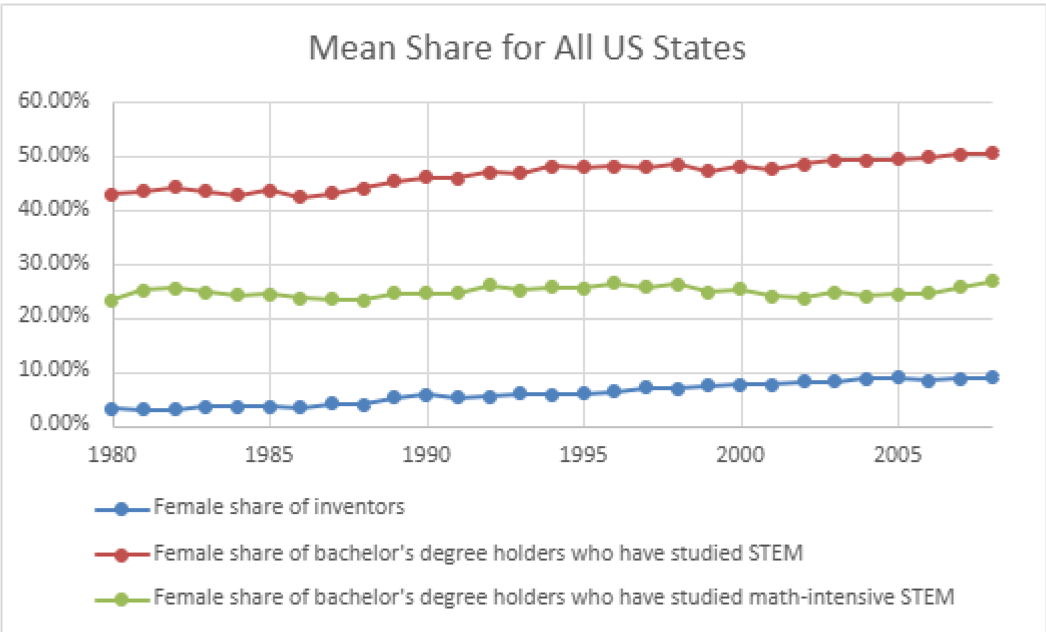
Note: Figure 3.2 summarizes the average female share of bachelor's degree holders who have studied STEM between the years 1980 and 2008. The states with the highest shares are Mississippi (53.48%), Arkansas (50.97%) and Kentucky (50.55%) and the states with the lowest shares are Utah (36.72%), Idaho (42.14%) and Wyoming (42.69%). Source: Authors' rendering of IPUMS USA data (2025).

Figure 3.3: Heat Map for the female share of bachelor's degree holders who have studied a math-intensive STEM for cohorts between 1980-2008 in the US.



Note: Figure 3.3 summarizes the average female share of bachelor's degree holders who have studied math-intensive STEM between the years 1980 and 2008. The highest shares are the states Mississippi (29.66%), District of Columbia (29.62%) and South Carolina (28.62%) and lowest shares are Utah (17.07%), Wyoming (20.66%) and Idaho (20.97%). Source: Authors' rendering of IPUMS USA data (2025).

Figure 3.4: The unweighted state-level mean for female shares for all US states, by cohorts.



Note: Figure 3.4 summarizes the unweighted state-level mean share for all US states where an increasing trend for all three variables could be observed across 1980-2008. Source: Authors' rendering of IPUMS USA data (2025) and USPTO data (2026).

4 Methodology

The methodology consists of an empirical strategy aimed at obtaining an unbiased estimate and consistent point estimates of the effect of role models on women's propensity to have studied STEM. The model of interest is a linear probability model (LPM) with the dependent variable whether a bachelor's degree holder has studied STEM in regression (4.1) and whether a bachelor's degree holder has studied math-intensive STEM in regression (4.2). The independent variables are gender and the share of female inventors. Regression (4.1) evaluates the effect of share of female inventors in state *g* being granted patents in cohort year *c* on the probability of a bachelor's degree holder in cohort *c* born in state *g* to have studied STEM and regression (4.2) evaluates the effect on female bachelor's degree holders' probability to have studied math-intensive STEM. The coefficient to the interaction term is β_3 which represents the differential effect in how much more likely a woman is to have studied STEM in regression (4.1), and math-intensive STEM in regression (4.2), if the share of female inventors increased in cohort *c* and birthplace *g*, compared to their male counterparts. The marginal effect could be calculated through summing β_1 and β_3. Control variables that might correlate with both the explanatory and dependent variables and cohort and state fixed effects are included to isolate the impact that the share of female inventors have on women who have studied STEM or math-intensive STEM, respectively. Table 4.1 depicts the variables in the regressions.

$$y_{\{icg\}} = \beta_0 + \beta_1 G_i + \beta_2 D_{icg} + \beta_3 G_i D_{icg} + \beta_4 X_{icg} + \delta_c + \alpha_g + \epsilon_{ic} \quad (4.1, 4.2)$$

Table 4.1: Definitions of the variables for the regressions.

Dependent Variable	
$y_{\{icg\}}$	Whether bachelor's degree holder *i* in cohort *c* born in state *g* has studied STEM (4.1) or math-intensive STEM (4.2).
Explanatory Variables	
D_{icg}	The share of female inventors in cohort *c* and state *g*, which bachelor's degree holder *i* belongs to and was born in.
G_i	Whether bachelor's degree holder *i* is a female.
Control Variables	
X_{icg}	A vector of control variables including unemployment rate, female college attendance and female labor force participation rate.
Fixed Effects	
δ_c	Cohort fixed effect for cohort *c*.
α_g	State fixed effect for state *g*.

Note: The subscripts i, c and g stand for bachelor's degree holder i, cohort c and state g which the bachelor's degree holder belongs to and was born in, respectively.

An LPM is suitable since the dependent variable is binary in our regressions, and the differential effect which is an interaction term is easily interpretable in a linear model, compared to logit and probit models. The probit and logit models are nonlinear and the magnitude of the interaction effect does not equate the marginal effect of the interaction term (Ai & Norton, 2003). In our LPM, patents are used as a proxy for inventors. Inventions and ideas, which are new ways of using existing resources, are key to sustaining economic growth in the long run. Therefore, it is important to incentivize the inventor, and one incentive is to grant patents for inventions. Patents provide the inventor with a temporary monopoly which allows the inventor to recoup the fixed costs in researching and developing the invention. This is the justification of patents which is one approach to encourage innovation, and why patents are a suitable proxy for inventors for studying this thesis' research question (Jones, 2020). The sectors that are more active in patenting consist of the STEM fields such as Mathematics, Physics, Chemistry, Medicine, Computer Science and Biology while the fields with patents with less extensive patenting activity include Psychology, Business, Economics, History and Philosophy, which underlines the importance of a strong STEM pipeline to boost innovation. Appendix A5 presents a figure with the patenting activity by sector (Yin et al., 2021).

An identifying assumption for causal inference in econometric analysis is conditional mean independence. Conditional mean independence is achieved when the estimation of the error term of observation *i* given the variable of interest and the control variables is not correlated with the variable of interest while it could depend on the control variables. As for the state and cohort fixed effects, the state fixed effects control for unobserved heterogeneity in panel data that are constant over time where time-constant and unit-specific differences are removed and the cohort fixed effects control for unobserved heterogeneity that changes over cohorts but is constant across states (Stock & Watson, 2020). Thus, the empirical method aims to capture factors that could be correlated with the variable of interest "Share of female inventors" including the female college attendance rate, female labor force participation rate and the unemployment rate as control variables. The great recession which caused high unemployment in the US influenced college major choices where individuals shifted toward choosing majors that were more resistant to economic recessions from those that were more sensitive to negative economic shocks. As the choice of education is important for an individual's future career path, students consider multiple factors when selecting majors at colleges, including how the labor market looks like graduating in a particular major or field. During the Great Recession, there was an increase in degrees in Psychology and Communication and Librarianship while there was a decrease in STEM majors including Sciences and Engineering Technologies (Ersoy, 2020). This is also one of the reasons this thesis only includes data until 2008 to avoid the estimates being affected by the Financial Crisis of 2008 which originated in the US and caused a significant global economic downturn (Trescott, 2023).

Furthermore, the female labor force participation rate is important to consider as it is associated with social norms and the implied gender gap in society. The progress in education system reforms, human capital accumulation and reduced discrimination has led to reduced gaps in labor force participation across genders. However, the narrowing of the gap has slowed during the last decade and the prevalent social norms influence an individual's behavior and education choices (Li et al., 2023). Moreover, female college attendance rates affect major choices. Female college attendance rate can reflect the expectations of women on their future employment (Goldin, 2024).

The state fixed effects control for unobserved heterogeneity including geography, historical institutions and long-standing cultural attitudes toward gender roles in society. Meanwhile, the cohort fixed effects account for trends affecting all states. For example, there might be a general trend in the US where more women start to attend college or a technology trend which could have inspired more women to pursue a bachelor's degree in STEM. Moreover, sample weights have been included from the IPUMS USA datasets due to different individuals having different likelihoods of being sampled (Ruggles et al., 2025). In our regressions, both the default standard errors and clustered robust errors are used. Clustered robust errors clustering on the state-level have been used to account for the within-cluster error correlation among individual observations within the states. Failing to control for this might cause misleadingly small standard errors and lead to large t-statistics and low p-values (Cameron & Miller, 2015).

To evaluate the internal validity of the results, multiple robustness tests were performed. The first robustness test evaluates whether the probability for a female bachelor's degree holder to have studied non-STEM degrees would be affected by the share of female inventors have been performed. This was achieved through regressing the probability of a female bachelor's degree holders to have studied certain non-STEM degrees as the dependent variable. Three non-STEM degree categories have been chosen for the robustness tests including Business or Law, Linguistics, Culture or History, and Physical Fitness, Parks, Recreation and Leisure. Another robustness test was to analyze the patent composition and evaluate whether medical patents would impact the probability of a bachelor's degree holder to have studied math-intensive STEM. Since the field of medicine does not involve heavy mathematics, it would be reasonable to expect no statistically significant relationship between the share of female medical patents and the probability of a female bachelor's degree holder to have studied math-intensive STEM. Additionally, we did a cohort sensitivity analysis to test whether the coefficient to the interaction term "Share female inventor x Female" would be significantly different from our baseline result when including different cohorts in our regression.

5 Results

5.1 Female Inventors and the Female Share in STEM

To evaluate the effect of the share of female inventors on the probability of an individual studying STEM, the following specifications in Table 5.1 have been produced: specification without fixed effects and control variables with default standard errors (1), specification with fixed effects and controls with default standard errors (2), specification without fixed effects and controls with clustered robust errors (3), specification with fixed effects but no control variables with clustered robust errors (4) and specification with fixed effects and control variables with clustered robust errors (5). The specification of interest is (5) where there are 1951617 observations included. The differential effect is the coefficient to the interaction term "Share female inventor x Female" which estimates the differential effect of which an increase in the share of female inventors has on the probability for a female bachelor's degree holder to have studied STEM compared to their male counterparts.

Table 5.1: Regression results for the effect of the share of female inventors on the probability of a bachelor's degree holder having studied STEM.

Dependent variable: Studied STEM

	(1)	(2)	(3)	(4)	(5)
Share female inventor	-0.306***	-0.256***	-0.306***	-0.244***	-0.256***
	(0.018)	(0.028)	(0.082)	(0.055)	(0.059)
Female	-0.107***	-0.107***	-0.107***	-0.107***	-0.107***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Share female inventor × Female	0.305***	0.296***	0.305***	0.297***	0.296***
	(0.024)	(0.024)	(0.059)	(0.059)	(0.059)
Unemployment rate		0.003***			0.003***
		(0.001)			(0.001)
Female LFP rate		0.106***			0.106**
		(0.031)			(0.050)
Female college rate		-0.045***			-0.045*
		(0.016)			(0.027)
Num.Obs.	1951617	1951617	1951617	1951617	1951617
R2	0.009	0.011	0.009	0.011	0.011
R2 Adj.	0.009	0.011	0.009	0.011	0.011
Clustered SE	No	No	Yes	Yes	Yes
State and Cohort FE	No	Yes	No	Yes	Yes
Controls	No	Yes	No	No	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Note: Table 5.1 summarizes the results of regression (4.1) which evaluates the effect of female inventors on the probability an individual having studied STEM. The differential effect "Share female inventor x Female" is significant across all specifications.

Interpreting the differential effect in specification (5), a one-percentage point increase in the share of female inventors is associated with an increase in the probability of a female college graduate to have studied STEM by 0.296 percentage points in cohort *c* and state *g* compared to their male counterparts and is statistically significant at a 1% significance level. Moreover, the estimate remains roughly the same magnitude comparing specification (5) to specifications before the fixed effects and control variables were added. This means that the control variables and fixed effects change the differential effect merely marginally. When the clustered robust errors are added in specifications (3), (4) and (5), the standard errors increase markedly compared to the default standard errors in specifications (1) and (2). Moreover, the marginal effect that an increase in the share of female inventors is associated with the likelihood of a woman with a bachelor's degree to have studied STEM is positive and can be computed through summing the estimate of interest "Share female inventor x Female" and the estimate to "Share female inventor". This gives that a one-percentage point increase in the share of female inventors is associated with a 0.040-percentage point increase in the likelihood of a female bachelor's degree holder to have studied STEM on average (0.296+(-0.256)), holding the control variables constant.

Furthermore, women bachelor's degree holders are on average 10.7 percentage points less likely to have studied STEM than their male counterparts on average and the estimate for "Female" is statistically significant at a 1% level. A one-percentage point increase in the female labor force participation rate is correlated with an increase by 0.106 percentage points for a bachelor's degree holder to have studied STEM. For the control variables female college attendance rate and unemployment rate, these two variables have barely any impact on the propensity of a bachelor's degree holder to have studied STEM.

5.2 Female Inventors and the Female Share in Math-Intensive STEM

Similarly to Section 5.1, to evaluate the share of female inventors on female bachelor's degree holders' probability to have studied math-intensive STEM, five specifications have been produced of regression (4.2) in Table 5.2: specification without fixed effects and controls with default standard errors (1), specification with fixed effects and controls with default standard errors (2), specification without fixed effects and controls with clustered robust errors (3), specification with fixed effects but no control variables with clustered robust errors (4) and specification with fixed effects and control variables with clustered robust errors (5). The specification of interest is (5) where there are 1939389 observations included. The differential effect is the coefficient to "Share female inventor x Female" which estimates the differential effect of which an increase in the share of female inventors have on a woman with a bachelor's degree to have studied math-intensive STEM, compared to their male counterparts.

To interpret the differential effect in specification (5), a one-percentage point increase in the share of female inventors is associated with an increase in the differential probability of a woman to have studied math-intensive STEM by 0.295 percentage points in cohort *c* and state *g* compared to their male counterparts. The estimate is statistically significant at a 1% significance level. The marginal effect of a one-percentage point increase in the share of female inventors is 0.098 percentage points increase in the likelihood of a female bachelor's degree holder to have studied math-intensive STEM on average (0.295+(-0.197)), which is more than double the magnitude compared to STEM.

Comparing specifications (1) to (5), the magnitudes of the differential effect "Share female inventors x Female" change only marginally as it did in Table 5.1 with overall STEM, which implies that the control variables and fixed effects have a little effect on the magnitude of the differential for a woman to have studied math-intensive STEM compared to the male counterpart.

Table 5.2: Regression results for the effect of share of female inventors on the probability of a bachelor's degree holder having studied math-intensive STEM.

Dependent variable: Studied Math-Intensive STEM

	(1)	(2)	(3)	(4)	(5)
Share female inventor	-0.425***	-0.197***	-0.425***	-0.191***	-0.197***
	(0.014)	(0.021)	(0.067)	(0.044)	(0.045)
Female	-0.190***	-0.189***	-0.190***	-0.189***	-0.189***
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
Share female inventor × Female	0.309***	0.295***	0.309***	0.295***	0.295***
	(0.018)	(0.018)	(0.057)	(0.057)	(0.058)
Unemployment rate		0.001**			0.001
		(0.000)			(0.001)
Female LFP rate		-0.056**			-0.056
		(0.024)			(0.037)
Female college rate		0.005			0.005
		(0.012)			(0.020)
Num.Obs.	1939389	1939389	1939389	1939389	1939389
R2	0.059	0.060	0.059	0.060	0.060
R2 Adj.	0.059	0.060	0.059	0.060	0.060
Clustered SE	No	No	Yes	Yes	Yes
State and Cohort FE	No	Yes	No	Yes	Yes
Controls	No	Yes	No	No	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Note: Table 5.2 summarizes the results from regression (4.2), which evaluates the effect of female inventors on the probability of an individual having studied math-intensive STEM. The differential effect "Share female inventor x Female" is significant across all specifications.

On average, female college graduates are 18.9 percentage points less likely to have studied math-intensive STEM compared to their male counterparts and the estimate for "Female" is statistically significant at a 1% level, which indicates that the gender gap for math-intensive STEM is almost double the gender gap for STEM where the gap was 10.7 percentage points (Section 5.1). The control variables female labor force participation rate, female college attendance rate and unemployment rate are not statistically significant at a 5% level.

5.3 Robustness Tests

To evaluate the internal validity of the results, multiple robustness tests have been performed. The robustness tests attempt to falsify the results through evaluating the effect of female inventors on the probability of a female bachelor's degree holder having studied non-STEM degrees, the share of female medical patents' impact on females to have studied math-intensive STEM and a cohort sensitivity analysis. The cohort sensitivity analysis is to evaluate whether including different cohorts in the regression would change the coefficient of the interaction term "Share female inventor x Female".

For the internal validity to hold, there should ideally be no positive statistically significant effect from share of female inventors on the probability of a female bachelor's degree holder to have studied a non-STEM degree. If the estimate is negative and statistically significant, it implies a substitution effect where individuals shift from non-STEM degrees to a STEM degree. Secondly, there should ideally not be a positive statistically significant effect of the share of female medical patents on the probability of a female bachelor's degree holder to have studied math-intensive STEM. Since medical patents is not a math-intensive field and often does not require an inventor to have studied a math-intensive STEM degree, an increase in the share of women in medical patents should not increase the propensity for women to have studied math-intensive STEM. Thirdly, the estimate of the differential effect "Share female inventor x Female" should not be significantly different from the baseline regression when including cohorts 1980, 1990, 2000 and 2008 (i), 1990, 2000-2008 (ii) and 2000-2008 (iii).

In addition, robustness tests for whether cumulative effects of the share of female patents would impact an individual's probability to have studied STEM and math-intensive STEM have been accounted for. To check whether the cumulative effect of which the choice of major could depend on the share of female inventors a few years before the students graduate from high school, the share of female inventors in the period *c-3 – c* have been averaged, in other words between the period three years before an individual graduate from high school and the year the individual graduate from high school. Cumulative effects are interesting since students in US high schools could explore advanced courses in mathematics and science including Advanced Placement (AP) courses. Students taking advanced one or two years of courses in calculus and physics and a second year of chemistry exhibit a stronger interest in STEM and a significantly higher interest in STEM careers compared to students who have not taken these courses. It is also shown that 10^{th} grade test scores have on average the largest impact on boosting college plans. Therefore, this thesis chooses to include the period *c-3* to *c*, where *c-3* is the year when the student is in grade 10 and *c* is the year when the student graduate from high school (Mineo, 2026; Sadler et al., 2014). However, due to the lack of data availability for control variables between 1981-1989 and 1991-1999, it was not possible to include cumulative effects for them. The results from the robustness test with cumulative effects should thus be interpreted with caution and can be found in Table 9.16 and Table 9.17 in Section Appendix A4.

Robustness Tests for Non-STEM Degrees

As for the robustness tests for non-STEM degrees, there are three different categories of non-STEM degrees in Table 5.3. All three specifications include fixed effects as well as control variables and consist of 1951617 observations. Specifications (1), (3) and (5) use default standard errors while specifications (2), (4) and (6) use clustered robust errors; the specifications of interest are the latter ones. For specifications (1) and (2), the non-STEM degrees include Business and Law, and specifications (3) and (4) include degrees within Linguistics, Culture or History, and specifications (5) and (6) contain the degree Physical Fitness, Parks, Recreation and Leisure.

Table 5.3: Robustness tests for various non-STEM degrees.

Dependent variable: Studied various non-STEM degrees

	(1)	(2)	(3)	(4)	(5)	(6)
Share female inventor	0.230***	0.230***	-0.039**	-0.039*	0.033**	0.033**
	(0.025)	(0.052)	(0.017)	(0.023)	(0.014)	(0.014)
Female	-0.047***	-0.047***	-0.006***	-0.006**	-0.001	-0.001
	(0.002)	(0.004)	(0.001)	(0.002)	(0.001)	(0.001)
Share female inventor × Female	-0.263***	-0.263***	0.035**	0.035*	-0.059***	-0.059***
	(0.022)	(0.047)	(0.015)	(0.020)	(0.014)	(0.014)
Unemployment rate	-0.000	-0.000	-0.000	-0.000	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Female LFP rate	0.016	0.016	0.040**	0.040*	0.032*	0.032*
	(0.028)	(0.043)	(0.019)	(0.022)	(0.019)	(0.019)
Female college rate	0.001	0.001	-0.028***	-0.028**	-0.007	-0.007
	(0.015)	(0.023)	(0.010)	(0.011)	(0.007)	(0.007)
Num.Obs.	1951617	1951617	1951617	1951617	1951617	1951617
R2	0.011	0.011	0.003	0.003	0.003	0.003
R2 Adj.	0.011	0.011	0.003	0.003	0.003	0.003
Clustered SE	No	Yes	No	Yes	No	Yes
State and Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Note: Table 5.3 summarizes the results for the robustness tests when having various non-STEM degrees as the dependent variable. The estimate of the differential effect "Share female inventor x Female" is negative and significant for specification (2) and (6), and for (4) it is not statistically significant at a 5% level.

The regression results in Table 5.3 indicate that a one-percentage point increase in the share of female inventors is correlated with a differential effect of the probability for a female college graduate to have studied Business or Law by -0.263, and Physical Fitness, Parks, Recreation and Leisure by -0.059 percentage points, compared to their male counterparts, and are statistically significant at a 1% level. The coefficients for the interaction term "Share female inventor x Female" in specifications (2) and (6) are negative and significant which explains a substitution effect where female college graduates have shifted from Business, Law and Physical Fitness, Parks, Recreation and Leisure to STEM degrees. For Linguistics, Culture or History, the differential effect in specification (4) is not significant at a 5% level. These results reaffirm the internal validity that an increase in the share of female inventors should not have a positive and significant impact on the differential propensity of female bachelor's degree holders to have studied STEM.

Moreover, the marginal effect could be calculated with the same method used in Sections 5.1 and 5.2. The marginal effect gives that a one-percentage point increase in the share of female inventors is associated with a change in the likelihood for a female bachelor's degree holder to have studied Business or Law by -0.033 (-0.263+0.230), Linguistics, Culture or History by -0.004 (0.035+(-0.039)) and Physical Fitness, Parks, Recreation and Leisure by -0.026 (-0.059+0.033). As the marginal effects for the placebo tests for the various non-STEM degrees are negative, it further strengthens the internal validity of our baseline results.

Robustness Tests for Medical Patents

In addition to the robustness tests for non-STEM degrees which focus on attempting to falsify the results through substituting the dependent variable, the robustness tests for medical patents endeavors to falsify the results through substituting the independent variable. In Table 5.4, five specifications have been produced with 1930542 observations; the explanation to each specification can be found in Sections 5.1 and 5.2.

Table 5.4: Outputs for the effect of the share of female medical patents on a female bachelor's degree holder to have studied math-intensive STEM.

Dependent variable: Studied Math-Intensive STEM					
	(1)	(2)	(3)	(4)	(5)
Share female inventor	-0.107***	-0.047***	-0.107***	-0.046***	-0.047***
	(0.006)	(0.007)	(0.030)	(0.016)	(0.016)
Female	-0.176***	-0.175***	-0.176***	-0.175***	-0.175***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Share female inventor × Female	0.075***	0.070***	0.075***	0.070***	0.070***
	(0.007)	(0.007)	(0.024)	(0.023)	(0.023)
Unemployment rate		0.001**			0.001
		(0.000)			(0.001)
Female LFP rate		-0.063***			-0.063
		(0.024)			(0.040)
Female college rate		0.004			0.004
		(0.012)			(0.020)
Num.Obs.	1930542	1930542	1930542	1930542	1930542
R2	0.058	0.060	0.058	0.060	0.060
R2 Adj.	0.058	0.060	0.058	0.060	0.060
Clustered SE	No	No	Yes	Yes	Yes
State and Cohort FE	No	Yes	No	Yes	Yes
Controls	No	Yes	No	No	Yes
* p < 0.1, ** p < 0.05, *** p < 0.01					

Note: Table 5.4 summarizes the regression output when regressing whether an individual has studied math-intensive STEM on the share of female medical patents.

It can be noted that the differential effect "Share female inventor x Female" is slightly positive at a magnitude of 0.070 and significant at a 1% level in specification (5). Although the estimate for this robustness test should ideally not be positive and significant, it is a fraction of the estimate for math-intensive STEM in Section 5.2 at 0.295, which is approximately 23.73% of that magnitude and these two estimates are statistically different from each other at a 95% confidence level. The marginal effect of a one-percentage point increase in the share of female inventors is correlated with a 0.023 (0.070+(-0.047)) percentage points increase in the probability of a female bachelor's degree holder to have studied math-intensive STEM. While the marginal effect is positive as well, it is around 23.47% of the magnitude of the marginal effect for math-intensive STEM in Section 5.2.

Cohort Sensitivity Analysis

In the cohort sensitivity analysis, six specifications have been produced in Tables 5.5 and 5.6. Specifications (1), (3) and (5) use default standard errors while specifications (2), (4) and (6) use clustered robust errors; the latter are the specifications of interest. Specification (1) and (2) include the cohorts 1980, 1990, 2000 and 2008; specifications (3) and (4) include the cohorts 1990, 2000-2008; specifications (5) and (6) include the cohorts 2000-2008. All specifications include fixed effects and control variables. It could be observed that the differential effect is not statistically different from the estimate in the baseline regressions at a 95% confidence level, which means that the baseline results are not sensitive to when certain cohorts are dropped or that the cohorts 2000-2008 are driving the results (Tables 5.5 and 5.6).

Table 5.5: Cohort sensitivity analysis for Regression (4.1).

Dependent variable: Studied STEM

	(1)	(2)	(3)	(4)	(5)	(6)
Share female inventor	-0.269***	-0.269***	-0.149***	-0.149**	-0.118***	-0.118
	(0.043)	(0.070)	(0.032)	(0.063)	(0.038)	(0.077)
Female	-0.110***	-0.110***	-0.096***	-0.096***	-0.091***	-0.091***
	(0.002)	(0.004)	(0.003)	(0.007)	(0.003)	(0.009)
Share female inventor × Female	0.271***	0.271***	0.186***	0.186**	0.139***	0.139
	(0.034)	(0.052)	(0.031)	(0.083)	(0.037)	(0.100)
Unemployment rate	0.004***	0.004**	0.002**	0.002	0.002***	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female LFP rate	0.083*	0.083	0.011	0.011	0.070	0.070
	(0.043)	(0.064)	(0.040)	(0.071)	(0.056)	(0.074)
Female college rate	-0.018	-0.018	-0.028	-0.028	-0.012	-0.012
	(0.026)	(0.042)	(0.017)	(0.021)	(0.018)	(0.023)
Num.Obs.	695758	695758	1768099	1768099	1597198	1597198
R2	0.014	0.014	0.011	0.011	0.010	0.010
R2 Adj.	0.014	0.014	0.011	0.011	0.010	0.010
Clustered SE	No	Yes	No	Yes	No	Yes
State and Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Note: Table 5.5 summarizes the results of the cohort sensitivity analysis for regression (4.1) where the dependent variable is whether a bachelor's degree holder has studied STEM. Observe that specification (1) and (2) include the cohorts 1980, 1990, 2000 and 2008; specifications (3) and (4) include the cohorts 1990, 2000-2008; specifications (5) and (6) include the cohorts 2000-2008.

Table 5.6: Cohort sensitivity analysis for Regression (4.2).

Dependent variable: Studied Math-Intensive STEM

	(1)	(2)	(3)	(4)	(5)	(6)
Share female inventor	-0.131***	-0.131**	-0.105***	-0.105*	-0.188***	-0.188**
	(0.034)	(0.055)	(0.024)	(0.059)	(0.029)	(0.072)
Female	-0.188***	-0.188***	-0.174***	-0.174***	-0.184***	-0.184***
	(0.002)	(0.004)	(0.002)	(0.006)	(0.003)	(0.008)
Share female inventor × Female	0.247***	0.247***	0.140***	0.140*	0.240***	0.240**
	(0.026)	(0.055)	(0.024)	(0.080)	(0.028)	(0.103)
Unemployment rate	0.002**	0.002*	-0.000	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female LFP rate	-0.068**	-0.068*	-0.127***	-0.127**	-0.046	-0.046
	(0.033)	(0.036)	(0.030)	(0.056)	(0.042)	(0.054)
Female college rate	0.054***	0.054*	0.006	0.006	0.007	0.007
	(0.020)	(0.030)	(0.013)	(0.017)	(0.013)	(0.017)
Num.Obs.	688594	688594	1757362	1757362	1586800	1586800
R2	0.062	0.062	0.058	0.058	0.058	0.058
R2 Adj.	0.062	0.062	0.058	0.058	0.058	0.058
Clustered SE	No	Yes	No	Yes	No	Yes
State and Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Note: Table 5.6 summarizes the results of the cohort sensitivity analysis for regression (4.2) where the dependent variable is whether a bachelor's degree holder has studied math-intensive STEM. Observe that specification (1) and (2) include the cohorts 1980, 1990, 2000 and 2008; specifications (3) and (4) include the cohorts 1990, 2000-2008; specifications (5) and (6) include the cohorts 2000-2008.

6 Discussion

The results suggests that there is a positive and statistically significant impact of the share of female inventors on the propensity of a female bachelor's degree holder to have studied STEM and math-intensive STEM at a bachelor's level. This is in line with most previous research, described in Sections 2.1 and 2.2. While we have studied the impact by role models on a broader level than most previous literature, namely the general US population on state level, this has been done at the expense of not having experimental variation and a causal relationship cannot be established.

6.1 Closing the Gender Gap in STEM

The aim of this thesis is to evaluate the effect of female role models on a female bachelor's degree holder's propensity to have studied STEM in the US. The results in Sections 5.1 and 5.2 have a statistically significant estimate of the differential effect "Share female inventors x Female". An increase in the share of female inventors is associated with an increase in the propensity for a female bachelor's degree holder to have studied STEM and math-intensive STEM. The magnitudes of the coefficients of interest are 0.296 and 0.295 for STEM and math-intensive STEM respectively. These findings, that female inventors can act as role models and thereby increase the propensity for female bachelor's degree holders to have studied STEM, is in line with findings by e.g. Carrell et al. (2010), Bottia et al. (2015) and Breda et al. (2023).

Moreover, the magnitudes of the marginal effects for STEM and math-intensive STEM are 0.040 and 0.098, respectively. This means that the marginal effect for math-intensive STEM is larger than the marginal effect for overall STEM. One possible reason behind this observation is that as the share of female bachelor's degree holders in math-intensive STEM is roughly half compared to overall STEM. As there are fewer women in math-intensive STEM, there could be potential for more female students to be inspired by an increasing share of female inventors to enter math-intensive STEM. It would be interesting to evaluate how much female inventors have contributed to more women in STEM between 1980 and 2008. As the national average share of female inventors has increased by 6.98-percentage points, the total effect of female inventors on the female share in STEM is 0.279 percentage points (0.040 * 6.98), and 0.684 percentage points (0.098 * 6.98) for math-intensive STEM. According to the descriptive statistics, the national average for the female bachelor's degree holders in STEM has increased 6.20 percentage points while math-intensive has increased 2.12 percentage points in that period. This means that female inventors contributed to 4.5% (0.279 / 6.20) and 32.3% (0.684 / 2.12) of the total increase in the female share of bachelor's degree holders who have studied STEM and math-intensive STEM, respectively. The contribution is much larger for math-intensive STEM than overall STEM, which is because of a larger marginal effect for and a smaller total increase in the female share in math-intensive STEM (see Section 3.2 for the descriptive statistics).

There could be a few reasons for our positive and significant results of the differential and marginal effect for both STEM and math-intensive STEM, such as (1) the self-fulfilling prophecy that Breda et al. (2023) describes, but in a positive spiral, i.e. if there are more female inventors there are more women for girls to be inspired by within STEM and therefore more girls might choose to have studied STEM, and the positive spiral continues. The female high school students could see the female inventors either from afar in newspapers or on firms' websites, or closer such as a woman with a firm backpack on the bus, a classmates mother or a neighbor; (2) according to Vooren et al. (2022), women have lower self-confidence and self-efficacy for STEM than men. Thus, more female inventors could mean that there are more inventors for females to be inspired by and that they can also succeed; (3) due to more female STEM workers, female students could be more protected from stereotypes, as is indicated by Lee et al. (2023).

These reasons are supported by for example Bell et al., (2019), who find that women are more likely to invent in the same area as the women in the neighborhood where they grew up in. This indicates that female inventors where an individual grows up can act as role models, even though they may not be in proximate relationships with the students and impact the share of female students who study STEM or math-intensive STEM. Furthermore, Olivetti et al. (2020) showed that the mothers of a woman's peers during her adolescence could influence her attitudes and expectations especially regarding motherhood and employment. This further indicates that the female inventors which a female student is exposed to during her childhood can impact her expectations regarding future employment and her career decisions. Additionally, Breda et al. (2023), found that brief guest lectures by women working in STEM influenced the choice of education and Carrell et al. (2010) found that the gender of the professor in a specific setting could even eliminate the gender gap within STEM. Furthermore, Bottia et al. (2015) finds that gender faculty composition at high schools impacts choice of major. Taken together, these papers indicate that female role models have an impact on the gender gap within STEM, that female inventors can act as role models and that the high school years of an individual can be highly influential for future choices of their education and thus supporting the validity of our results.

The coefficient estimates for the variable "Share of female inventors" are negative and statistically significant for the baseline regressions for STEM and for math-intensive STEM in Sections 5.1 and 5.2. This implies that a higher share of female inventors is associated with a lower propensity for male bachelor's degree holders to have studied STEM and math-intensive STEM. Ideally, there would be no effect of more female role models on men's probability to have studied STEM. This could possibly be due to share of male inventors, i.e. share of potential role models based on gender, decreasing. Notably though, Mansour et al. (2022) also found a negative relationship between female role models and the probability of a man to study a STEM master's degree and participate in the STEM workforce. However, as previously mentioned, the marginal effect of share of female inventors on the propensity for a woman with a bachelor's degree to have studied STEM and math-intensive STEM is positive. In Table 5.1, only the female labor force participation rate had a material impact on the probability whether a bachelor's degree holder have studied STEM. The female labor force participation rate which has a positive effect on the probability of a bachelor's degree holder having studied STEM is reasonable. A higher female labor participation rate is typically associated with social norms where women are encouraged to work which incentivizes individuals to study STEM (Li et al., 2023).

Closing the gender gap is highly relevant in multiple aspects. The gender gap within innovation is concerning as thousands of female-focused inventions are missing. This is partially because of the lack of women inventors as they are more likely to invent for women in technology fields relating to for example women's health. Patents by inventor teams with only women are 35% more likely to focus on women's health than by teams with only men (Koning et al., 2021). While women represent half of the US population, only 10 percent of US patent inventors are women (Jensen et al., 2018). Lubczyk and Moser (2025), finds that for every five women entering STEM, one additional woman becomes an inventor. In other words, breaking the trend in OECD countries of the plateau in the increase of women in STEM is of importance not only for aggregate productivity and gender wage gap, but also for finding inventions for women.

The robustness tests indicate that there are no positive and significant effects on bachelor's degree holders' propensity to have studied various categories of non-STEM degrees which strengthens the internal validity of this study. Meanwhile, there is a small, significant and positive effect for medical patents on the propensity of female bachelor's degree holders to have studied math-intensive STEM. While an increase in the female share in medical patents is typically not expected to boost the probability of female students in math-intensive STEM, this could indicate a sort of spillover effect. Women patenting in the medical sector might still inspire female students and enhance their self-confidence for STEM in general which can be connected to the literature about role models' impact on self-efficacy in Section 2.2, such as Lee et al. (2023). Furthermore, the cohort sensitivity analysis strengthens the internal validity as the coefficients of interest in the regressions when including the cohorts 1980, 1990, 2000 and 2008 (i), 1990 and 2000-2008 (ii), and 2000-2008 (iii) do not differ significantly from the baseline regression at a 95% confidence level.

Our study finds that an increasing share of female inventors is associated with higher share of female bachelor's degree holders to have studied both STEM and math-intensive STEM. The increasing female share of inventors have contributed 4.5% and 32.3% in increasing the share of female bachelor's degree holders who have studied STEM and math-intensive STEM respectively. The implications for policymakers have two aspects. The first is that policies targeted at increasing the exposure to female inventors for female students could increase their propensity to study STEM. As the figures indicate, exposure to female role models could have contributed significantly to reduce the gender gaps in math-intensive STEM. One advantage with increasing exposure to female inventors is that the treatment could be on a broader population, unlike classroom interventions. However, female inventors are only one factor that have contributed to the increasing trend of females in STEM and there could be other factors such as female teachers in STEM who could have had a larger impact in reducing this gender gap. As such, there is potential for further research which will be discussed more thoroughly in Section 6.3.

6.2 Limitations

Although our results might give insights into how role models could contribute to closing the gender gap within STEM, there are several limitations with our study. Firstly, in contrast to the previous literature, such as Carrell et al. (2010), a limitation of our methodology is that a causal relationship cannot be established due to the lack of experimental and exogenous variation. As such, the residual variation of the dependent variable, whether an individual studied STEM or math-intensive STEM, is likely not "as good as random" and a causal inference cannot be established. As we cannot make a causal inference, the mechanism of the increasing share of females in STEM could not with certainty to be said be attributed to the increase of the female share of inventors. It could be other factors such as social norms and expectations which drives the increase in both the share of female inventors and female students in STEM. Secondly, there are limitations with an LPM such as heteroskedastic errors, which is why the specification of interest uses robust errors to mitigate this problem. The LPM also assumes linear relationships between the dependent and independent variables. There could be the possibility that the slope coefficient or the differential effect of an increase in the female share of inventors on the propensity of a female bachelor's degree holder having studied STEM differs across various levels of the female share of inventors.

Third, an assumption when using fixed effects is strict exogeneity, which means that the residual term cannot be correlated with the independent variable which is the share of female inventors in the given, past or future cohort For any given cohort, this research design evaluates the female share of inventors in cohort year *c's* impact on the share of women who have studied STEM during the same year when the individuals made the choice of college major at their universities. This makes it unlikely that the share of female inventors could have been impacted by the share of women who have studied STEM during the same cohort year. However, for individuals in the latter cohorts, the residual variation might be correlated with the share of female bachelor's degree holders who have studied STEM in earlier cohorts as the female bachelor's degree holders in e.g. cohort 1980 might have become inventors and inspired another individual in the 2008 cohort to have studied STEM. Moreover, a concern could be that people select which state to live in which would be subject to endogeneity concerns with self-selection. However, this self-selection should not be a problem. The state where an individual is born in is essentially a random event as the birthplace cannot be impacted by the individual and two-thirds of 18-29 year olds have reported that they have never moved out of the state they were born in (Taylor et al., 2008).

Furthermore, even though some confounding factors have been included, there can still be several confounding factors that have been omitted. One potential omitted variable is the socioeconomic status of the individuals' states when they grew up before they started university. Included in the contextual-level factors that Evagorou et al. (2024) describes as one of the factors for the gender gap within STEM, is social class. The socioeconomic status (SES) of parents shapes a student's sociocultural capital, which relates to science and cultural knowledge, resources and experiences of the individual. This means that the probability of a student pursuing a science career is lower for students with a lower SES background. Additionally, one of the birth characteristics affecting probability of becoming an inventor is socioeconomic status according to Bell et al. (2019). The general socioeconomic status of parents could differ between states and therefore be correlated with the share of female inventors and be a determinant of whether a female student studied STEM. Thus, omitting parents' SES for the different states has probably led to positive bias in our result and this weakens the internal validity of our study. Another potentially omitted factor is math and spatial skills on state level. For both Bottia et al. (2015) and Carrell et al. (2010), there was a larger impact by the female role models for female students with high math skills. According to Tian et al. (2023), math achievement robustly predicts the choice of STEM majors within gender and that spatial skills could indirectly predict STEM major choice as well. Spatial skills are useful when visualizing objects in space and are crucial to succeeding in many STEM disciplines such as mathematics, chemistry and engineering. According to Bell et al. (2019), math skills are also predictive of innovation rates.

Other potential omitted variables include the quality of schools and universities, and the industry composition within the states. Schools with higher quality and supportive STEM faculties would be expected to have a positive effect on the share of women who have studied STEM. Institutions focusing more heavily on undergraduate education are better at retaining their students in STEM. On the contrary, selective colleges with large R&D expenditure relative to total educational expenditure tend to have a lower persistence rate, especially for minority students (Griffith, 2010). Another interesting example is the Experimental Study Group (ESG) at MIT which features small classes and teaching methods that differ from the mainstream versions in the introduction classes. These classes have the purpose to make the transition for female and minority groups to MIT easier. Although the results are noisy, the students participating in the program benefit from these learning communities. The women participating in the ESG program obtain higher GPAs and more credits of coursework (Russell, 2017). The industry composition in the states could be interesting as well since a state that is more specialized in manufacturing compared another state that is specialized in developing high-end technology would produce different labor market outcomes and different education choices among the individuals in that state.

Additionally, there are limitations with the data we used. Due to the nature of the IPUMS USA datasets, state was the most local level available for where an individual grew up. However, as the states of the US are quite large with a broad possible variation within states, it would have been ideal with data on a more local level such as commuting zones, as Bell et al. (2019) exploited. The state level might give a more biased result than commuting zones. For example, inventors might be clustered around certain regions within a state. An individual could grow up far from these regions, but still within the same state, and might not be aware of those female inventors. One way to check if this caused a problem is to investigate if the female inventors were clustered around e.g. metropolitan areas of the states. If female inventors were clustered around these metropolitan areas, we ideally would have wanted to test a specification only including observations from the metropolitan areas. However, as the IPUMS USA does not provide data on whether an individual's birthplace is in a metropolitan area within a state, this would not have been feasible.

There is also a limited amount of data which did not enable us to include the cohorts for the years 1981-1989 and 1991-1999 as well as years after 2008, which could be interesting for evaluating this research question. Additionally, the cohort assumes that all students graduate from high school at 18 which does not necessarily hold as students could graduate at another age (see Section 3.3). In addition, there could be cumulative effects of the share of female patents on an individual's probability to have studied STEM and math-intensive STEM. Cumulative effects are interesting since students in US high schools could explore advanced courses in mathematics and science including Advanced Placement (AP) courses. Students taking advanced one or two years of courses in calculus and physics and a second year of chemistry exhibit a stronger interest in STEM and a significantly higher interest in STEM careers compared to students who have not taken these courses (Sadler et al., 2014). However, as the data for the control variables female labor force participation rate and college rate was missing for the years 1981-1989 and 1991-1999, it was not possible to include the cumulative effects for the control variables. Therefore, the results for the cumulative effects in this thesis should be interpreted with caution (see Table 9.16 and 9.17 in Appendix A4).

Lastly, the latest cohort year included in our study is 2008, which is almost two decades ago. Ideally, more recent cohort years should have been included to have a higher predictive power for the coming years' STEM graduates to inform policymakers. This is because the relationship between female inventors and female students in STEM could be different in the last decade compared to a few decades ago. Another consideration is the Financial Crisis which occurred in 2008. The Financial Crisis caused a Great Recession and the World GDP to decline in 2009 for the first time in decades and the unemployment rate peaked at 10% (Jones, 2020). Therefore, it could be interesting to test for including and excluding cohorts around 2008 to see if the recession had a significant impact on the choice of college degree.

6.3 Further Research

This thesis has endeavored to evaluate how female inventors could affect female student's propensity to study STEM in bachelor's degree programs in the US. However, there is potential for further research. Firstly, this type of research could be conducted in an experimental environment. One of the limitations of our thesis is the lack of experimental variation in our data and not being able to establish a causal inference for the effect of female inventors on female student's propensity to study STEM. An experiment could be a randomized control trial (RCT) over a period of 5-10 years on different high schools in the US. The purpose of conducting the experiment over an extended period is to capture the effect of exposure to female inventors over time and for multiple cohorts. For this experiment, a sufficiently large number of high schools must be selected, and the high schools would be randomized into a control and treatment group, where the treatment group would have a higher exposure to female inventors than the control group. When randomizing high schools into these two groups, it is imperative to ensure that these groups are balanced, meaning that they should share similar characteristics so that ideally the only variation between the two groups is the level of exposure to female inventors. For the treatment group, to have a high exposure to female inventors, a suggestion would be to name classrooms and laboratory equipment after female inventors. For example, DNA equipments could be named after Rosalind Franklin who contributed with her discovery of the double helix structure of DNA (Rosalind Franklin University, n.d.). Another example could be to name a computer classroom after Ada Lovelace, who wrote the algorithm for the first computer program (Max-Planck-Gesellschaft, n.d.). One difference between this experiment and our study is that we study contemporary inventors evaluating patents granted the same year as a student starts university while Rosalind Franklin and Ada Lovelace belong to historical scientists and engineers.

Another possible methodology for causal inference would be a quasi-experimental methodology similar to Bell et al. (2019). While that article studies who becomes an inventor, it could be interesting to replicate their methodology for the effect of childhood environment to study who becomes a STEM graduate. To replicate their study, a dataset with individuals who have studied STEM which can be matched to parents' tax records would be needed. In other words, the data we have used from IPUMS USA would not be possible to use, as it is anonymized. Through the parents' tax records, it is possible to identify when and where the STEM students moved during their childhood, based on the ZIP code the parents filed their taxes from. The channel would be exposure to the regions with a higher share of female inventors and thus the age of when an individual moved is what matters as that implies a longer exposure to the region. The method could capture how the propensity for a female student to study STEM varies with her age when she moved to an area with a higher share of female inventors.

While our thesis focuses on measuring role model's effect on female students choosing STEM as their college degree in the US, there is potential for further research. For example, it would be interesting to analyze other role models than inventors such as teachers who could also have a large impact on students as they are regularly meeting the students. While this has been done at e.g. the US Air Force Academy by Carrell et al. (2010) and at high schools in North Carolina by Bottia et al. (2015), it would be interesting to investigate high school teachers and the effect to the general US population in other states on female student's choosing STEM. Another possible independent variable could be share of female STEM workers, classified by occupations. They could also act as role models in a similar way as female inventors. It would also be interesting to evaluate how cultural attitudes and norms toward gender roles affect female individual's propensity to study STEM. While this study was conducted on data in the US, and it would be interesting to replicate this study in European countries, where the EU has made a priority to close the STEM gender gap in its education policy (Zamfir, 2026).

Furthermore, it could be interesting to analyze the historical influence by female STEM role models. Di Addario et al. (2024) investigates if the underrepresentation of women in Italy is stemming from social norms during the Middle Ages through information of founders of Medieval guilds and Lubczyk and Moser (2025) investigate whether the innovation gender gap can be closed through changes in the allocation of talent through exploiting an exogenous shock, namely World War II. With historical patent data for the US, further research could investigate whether states in the US where there historically have been more female inventors, also still today have more STEM students.

7 Conclusion

In conclusion, this thesis has evaluated the research question whether female role models affect the propensity of female individual's choice of studying STEM and math-intensive STEM in bachelor's degree programs in the US. The gender gap within STEM could be tied to the literature about self-efficacy and self-fulfilling prophecy, where female students become inspired to study STEM and more confident in their abilities when there are more female inventors acting as their role models. Closing the gender gap is important from both a gender wage gap aspect, as STEM occupations have higher salaries and smaller wage gaps, and an economic aspect as innovations and ideas to sustain economic growth, and a gender gap would potentially result in economic output loss. There are also confounding factors such as female labor force participation and unemployment rate which have been controlled for in the regressions.

To evaluate our research question, we have retrieved data from the IPUMS USA, the U.S. Bureau of Labor Statistics (BLS) and the United States Patent and Trademark Office (USPTO), including the cohorts 1980, 1990 and between 2000 and 2008. The methodology being employed is a linear probability model (LPM) including control variables and fixed effects using clustered robust errors. The results suggest that a one-percentage point increase in the female share of inventors is associated with 0.296 percentage points and 0.295 percentage points increase in the differential probability that a female bachelor's degree holder has studied STEM and math-intensive STEM respectively compared to their male counterparts. Both estimates are statistically significant at a 1% level. Additionally, the marginal effects on the propensity of a female bachelor's degree holder to have studied STEM or math-intensive STEM of a one percentage point increase in the share of female inventors is 0.040 percentage points and 0.098 percentage points, respectively. Female inventors have contributed to increasing the female share in STEM by 4.5% and in math-intensive STEM by 32.3% between 1980 and 2008. Furthermore, the robustness tests support that the results are robust to different specifications and falsifications. An increase in the share of female inventors is not associated with an increase in various categories of non-STEM degrees such as Business or Law, which could strengthen the internal validity of this study. This suggests that there could be role model effects affecting female bachelor's degree holders' propensity to have studied STEM in bachelor's degree programs in the US. As for policy implications, policymakers could consider efforts to make female inventors more salient through various channels to encourage more female students to study STEM. However, since female inventors are unlikely to be the only factor that increases the female share in STEM, other channels that may contribute to this trend such as increasing the share of female teachers in STEM could be interesting to evaluate as well.

Meanwhile, the reader should acknowledge the limitations with this study, including missing data for the control variables female college attendance rate and female labor force participation rate between the period 1981-1989 and 1991-1999. Since the data lacks experimental variation, it is not possible to establish a causal link due to endogeneity problems with for example reverse causality and omitted variable bias. Therefore, there is clear potential for how this study could be improved. Finally, regarding future research, it could be interesting to conduct this study in European countries.

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9 Appendix

A1 State Abbreviations

Table 9.1: Abbreviations list for the US states.

State	Abbreviation
Alabama	AL
Alaska	AK
Arizona	AZ
Arkansas	AR
California	CA
Colorado	CO
Connecticut	CT
Delaware	DE
District of Columbia	DC
Florida	FL
Georgia	GA
Hawaii	HI
Idaho	ID
Illinois	IL
Indiana	IN
Iowa	IA
Kansas	KS
Kentucky	KY
Louisiana	LA
Maine	ME
Maryland	MD
Massachusetts	MA
Michigan	MI
Minnesota	MN
Mississippi	MS
Missouri	MO
Montana	MT
Nebraska	NE
Nevada	NV
New Hampshire	NH
New Jersey	NJ
New Mexico	NM
New York	NY
North Carolina	NC
North Dakota	ND
Ohio	OH
Oklahoma	OK
Oregon	OR
Pennsylvania	PA
Rhode Island	RI
South Carolina	SC
South Dakota	SD
Tennessee	TN
Texas	TX
Utah	UT
Vermont	VT
Virginia	VA
Washington	WA
West Virginia	WV
Wisconsin	WI
Wyoming	WY

Note: Table 9.1 summarizes the two-letter abbreviations for the states in the US. Source: United States Postal Service (2019).

A2 Classification of Degreefields

Table 9.2: Classifications of degreefields into STEM and math-intensive STEM.

Degreefield	STEM	Math-Intensive STEM
N/A	2	2
Agriculture	0	0
Environment and Natural Resources	1	0
Architecture	1	0
Area, Ethnic, and Civilization Studies	0	0
Communications	0	0
Communication Technologies	1	1
Computer and Information Sciences	1	1
Cosmetology Services and Culinary Arts	0	0
Education Administration and Teaching	0	0
Engineering	1	1
Engineering Technologies	1	1
Linguistics and Foreign Languages	0	0
Family and Consumer Sciences	0	0
Law	0	0
English Language, Literature, and Composition	0	0
Liberal Arts and Humanities	0	0
Library Science	0	0
Biology and Life Sciences	1	0
Mathematics and Statistics	1	1
Military Technologies	1	1
Interdisciplinary and Multi-Disciplinary Studies (General)	0	0
Physical Fitness, Parks, Recreation, and Leisure	0	0
Philosophy and Religious Studies	0	0
Theology and Religious Vocations	0	0
Physical Sciences	1	1
Nuclear, Industrial Radiology, and Biological Technologies	1	1
Psychology	0	0
Criminal Justice and Fire Protection	0	0
Public Affairs, Policy, and Social Work	0	0
Social Sciences	0	0
Construction Services	0	0
Electrical and Mechanic Repairs and Technologies	1	1
Precision Production and Industrial Arts	0	0
Transportation Sciences and Technologies	1	1
Fine Arts	0	0
Medical and Health Sciences and Services	1	0
Business	0	0
History	0	0

Note: Table 9.2 summarizes the full classifications of degreefields for whether they are STEM or math-intensive STEM respectively. The values 0, 1 and 2 have been assigned to if the subject is not STEM, if the degreefield is STEM and math-intensive STEM, and if the value is missing respectively. The degreefields have been classified according to Homeland Security Investigations (2024), Luo et al. (2022) and Ruggles et al. (2025). Psychology was classified as non-STEM as women represent a large majority of psychology students (Fowler et al., 2018).

A3 Descriptive and Summary Statistics

Table 9.3: The raw observations from the first IPUMS USA dataset.

Statistic	Observations
States	**51**
Cohorts	**11**
Individuals	**5641087**
Men	2835679
Women	2805408
College Graduates	**1973310**
Studied STEM	**1621491**
Men	869640
Women	751851
Studied Math-Intensive STEM	**266609**
Men	199627
Women	66982

Note: Table 9.3 summarizes the number of observations from the first IPUMS USA dataset consisting of the ACS 2009-2024, including all 50 states and DC in the cohorts 1980, 1990, 2000-2008. Source: Authors' rendering of IPUMS USA data (2025).

Table 9.4: The share of female inventors by state and cohort.

State	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
AK	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.06	0.05	0.06	0.09	0.23	0.00	0.00	0.13	0.00	0.09	0.00	0.12	0.12	0.00	0.06	0.06
AL	0.01	0.08	0.01	0.08	0.04	0.02	0.04	0.07	0.06	0.04	0.04	0.04	0.03	0.04	0.06	0.05	0.03	0.05	0.07	0.08	0.11	0.06	0.10	0.09	0.08	0.06	0.08	0.08	0.10
AR	0.02	0.11	0.00	0.00	0.00	0.03	0.00	0.07	0.00	0.02	0.06	0.08	0.03	0.05	0.03	0.06	0.01	0.03	0.04	0.08	0.02	0.09	0.06	0.08	0.08	0.09	0.07	0.11	0.09
AZ	0.03	0.03	0.02	0.00	0.03	0.06	0.02	0.04	0.02	0.05	0.03	0.03	0.05	0.06	0.06	0.06	0.05	0.06	0.05	0.05	0.06	0.07	0.06	0.06	0.06	0.09	0.08	0.08	0.07
CA	0.03	0.03	0.03	0.04	0.04	0.04	0.04	0.05	0.06	0.06	0.06	0.07	0.07	0.07	0.06	0.07	0.08	0.08	0.08	0.09	0.09	0.09	0.09	0.09	0.09	0.10	0.09	0.10	0.10
CO	0.04	0.03	0.02	0.00	0.05	0.02	0.03	0.05	0.03	0.04	0.05	0.03	0.05	0.05	0.07	0.06	0.08	0.08	0.08	0.08	0.08	0.07	0.08	0.09	0.08	0.09	0.09	0.08	0.10
CT	0.02	0.02	0.03	0.03	0.03	0.04	0.04	0.04	0.05	0.05	0.06	0.06	0.06	0.07	0.06	0.07	0.06	0.08	0.08	0.08	0.07	0.10	0.12	0.12	0.13	0.14	0.12	0.11	0.11
DC	0.03	0.03	0.04	0.03	0.04	0.05	0.03	0.05	0.06	0.06	0.08	0.07	0.07	0.07	0.08	0.09	0.09	0.10	0.09	0.11	0.10	0.09	0.11	0.11	0.11	0.11	0.13	0.15	0.12
DE	0.03	0.03	0.03	0.03	0.05	0.04	0.05	0.04	0.05	0.09	0.06	0.07	0.07	0.07	0.06	0.07	0.06	0.07	0.08	0.08	0.07	0.09	0.09	0.09	0.10	0.11	0.11	0.12	0.12
FL	0.02	0.03	0.02	0.02	0.04	0.03	0.03	0.03	0.04	0.05	0.05	0.04	0.05	0.04	0.07	0.07	0.07	0.07	0.07	0.07	0.06	0.07	0.06	0.07	0.07	0.06	0.06	0.07	0.08
GA	0.02	0.03	0.01	0.09	0.05	0.05	0.02	0.03	0.03	0.04	0.04	0.05	0.04	0.07	0.04	0.05	0.05	0.07	0.08	0.06	0.08	0.09	0.06	0.07	0.08	0.08	0.09	0.09	0.09
HI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.04	0.05	0.00	0.04	0.04	0.04	0.08	0.02	0.07	0.11	0.12	0.05	0.17	0.15	0.12	0.24	0.12	0.06	0.14
IA	0.02	0.00	0.04	0.03	0.02	0.02	0.02	0.05	0.02	0.03	0.05	0.06	0.04	0.04	0.06	0.05	0.05	0.04	0.06	0.06	0.07	0.09	0.09	0.11	0.08	0.08	0.08	0.11	0.10
ID	0.02	0.00	0.00	0.02	0.04	0.03	0.06	0.00	0.00	0.05	0.03	0.06	0.09	0.04	0.05	0.05	0.03	0.04	0.04	0.04	0.06	0.04	0.05	0.05	0.05	0.06	0.06	0.07	0.06
IL	0.02	0.03	0.02	0.03	0.03	0.03	0.04	0.03	0.04	0.05	0.05	0.06	0.06	0.07	0.07	0.06	0.07	0.08	0.07	0.08	0.08	0.09	0.10	0.08	0.08	0.08	0.09	0.08	0.09
IN	0.04	0.04	0.03	0.04	0.03	0.05	0.04	0.06	0.07	0.06	0.06	0.05	0.04	0.06	0.05	0.06	0.08	0.07	0.07	0.08	0.07	0.09	0.09	0.08	0.09	0.08	0.10	0.12	0.12
KS	0.02	0.00	0.01	0.04	0.01	0.02	0.05	0.03	0.05	0.05	0.06	0.07	0.06	0.07	0.04	0.04	0.05	0.04	0.08	0.08	0.07	0.09	0.11	0.10	0.08	0.11	0.05	0.11	0.08
KY	0.01	0.02	0.04	0.04	0.01	0.01	0.05	0.03	0.01	0.05	0.03	0.04	0.04	0.03	0.02	0.03	0.03	0.05	0.06	0.08	0.07	0.06	0.08	0.08	0.06	0.09	0.08	0.07	0.11
LA	0.01	0.03	0.06	0.05	0.04	0.04	0.08	0.06	0.05	0.03	0.03	0.03	0.04	0.03	0.02	0.04	0.05	0.03	0.04	0.04	0.06	0.05	0.07	0.06	0.09	0.07	0.06	0.07	0.13
MA	0.02	0.03	0.03	0.03	0.04	0.04	0.03	0.05	0.05	0.05	0.06	0.07	0.07	0.07	0.08	0.08	0.09	0.10	0.10	0.09	0.09	0.10	0.09	0.09	0.09	0.10	0.11	0.10	0.10
MD	0.02	0.03	0.04	0.05	0.04	0.06	0.04	0.03	0.06	0.05	0.04	0.07	0.07	0.07	0.09	0.07	0.08	0.08	0.10	0.10	0.10	0.10	0.10	0.10	0.11	0.10	0.09	0.09	0.12
ME	0.05	0.04	0.00	0.03	0.03	0.06	0.00	0.12	0.04	0.02	0.07	0.05	0.01	0.07	0.06	0.04	0.05	0.06	0.11	0.03	0.05	0.04	0.10	0.12	0.10	0.13	0.15	0.15	0.10
MI	0.04	0.03	0.04	0.04	0.04	0.05	0.05	0.04	0.05	0.04	0.05	0.04	0.05	0.06	0.05	0.06	0.06	0.06	0.07	0.06	0.05	0.06	0.06	0.07	0.07	0.07	0.07	0.08	0.09
MN	0.02	0.03	0.03	0.04	0.04	0.04	0.05	0.04	0.05	0.05	0.05	0.06	0.07	0.08	0.08	0.07	0.08	0.09	0.09	0.09	0.08	0.09	0.09	0.09	0.08	0.08	0.08	0.09	0.09
MO	0.02	0.03	0.02	0.03	0.03	0.03	0.02	0.04	0.04	0.04	0.04	0.04	0.07	0.05	0.06	0.07	0.07	0.08	0.08	0.07	0.09	0.08	0.10	0.10	0.13	0.11	0.12	0.10	0.10
MS	0.00	0.00	0.17	0.04	0.07	0.03	0.00	0.11	0.00	0.02	0.03	0.03	0.02	0.04	0.03	0.03	0.05	0.04	0.05	0.11	0.11	0.06	0.14	0.10	0.09	0.06	0.07	0.06	0.07
MT	0.12	0.07	0.09	0.00	0.11	0.04	0.06	0.00	0.00	0.00	0.02	0.00	0.01	0.10	0.03	0.03	0.07	0.06	0.03	0.10	0.05	0.10	0.06	0.06	0.06	0.08	0.07	0.07	0.09
NC	0.04	0.06	0.04	0.03	0.06	0.03	0.06	0.04	0.06	0.09	0.07	0.07	0.10	0.08	0.09	0.07	0.09	0.10	0.08	0.10	0.10	0.09	0.10	0.10	0.10	0.09	0.09	0.10	0.09
ND	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.12	0.09	0.10	0.05	0.05	0.15	0.06	0.02	0.04	0.14	0.03	0.07	0.16	0.10	0.02	0.07	0.11	0.12	0.05	0.08	0.08
NE	0.02	0.02	0.04	0.03	0.05	0.01	0.05	0.05	0.05	0.04	0.05	0.03	0.02	0.03	0.03	0.03	0.03	0.04	0.03	0.03	0.04	0.07	0.04	0.11	0.07	0.08	0.07	0.04	0.09
NH	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.02	0.04	0.03	0.03	0.02	0.01	0.03	0.02	0.05	0.04	0.06	0.05	0.08	0.06	0.05	0.04	0.04	0.04	0.05	0.06	0.05	0.06
NJ	0.04	0.04	0.04	0.04	0.06	0.04	0.05	0.05	0.07	0.07	0.07	0.09	0.09	0.09	0.09	0.10	0.10	0.10	0.11	0.11	0.10	0.10	0.11	0.11	0.11	0.11	0.12	0.13	0.13
NM	0.05	0.00	0.00	0.21	0.05	0.00	0.10	0.00	0.11	0.06	0.07	0.08	0.07	0.04	0.05	0.05	0.05	0.08	0.06	0.08	0.09	0.06	0.08	0.09	0.07	0.11	0.11	0.10	0.06
NV	0.07	0.04	0.00	0.10	0.02	0.03	0.00	0.00	0.02	0.16	0.01	0.07	0.05	0.03	0.06	0.06	0.08	0.06	0.04	0.05	0.05	0.05	0.06	0.07	0.11	0.10	0.12	0.09	0.12
NY	0.03	0.03	0.03	0.04	0.04	0.05	0.05	0.06	0.06	0.07	0.07	0.06	0.07	0.07	0.07	0.08	0.07	0.09	0.09	0.09	0.10	0.09	0.09	0.10	0.11	0.11	0.11	0.11	0.11
OH	0.02	0.03	0.02	0.03	0.03	0.03	0.03	0.05	0.03	0.04	0.05	0.05	0.06	0.06	0.06	0.06	0.07	0.08	0.09	0.09	0.09	0.09	0.08	0.09	0.10	0.09	0.09	0.11	0.09
OK	0.01	0.03	0.02	0.02	0.03	0.03	0.03	0.03	0.04	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.05	0.07	0.07	0.07	0.08	0.07	0.09	0.08	0.06	0.08	0.05	0.05
OR	0.02	0.04	0.04	0.01	0.04	0.02	0.03	0.07	0.08	0.06	0.03	0.04	0.05	0.07	0.08	0.05	0.05	0.06	0.05	0.06	0.06	0.07	0.05	0.06	0.06	0.08	0.09	0.08	0.07
PA	0.02	0.03	0.03	0.03	0.04	0.03	0.04	0.04	0.05	0.05	0.04	0.05	0.06	0.06	0.06	0.08	0.07	0.08	0.09	0.10	0.10	0.11	0.10	0.08	0.09	0.09	0.09	0.10	0.09
RI	0.03	0.03	0.01	0.02	0.01	0.03	0.07	0.10	0.04	0.04	0.04	0.04	0.06	0.05	0.09	0.10	0.08	0.06	0.08	0.05	0.09	0.07	0.09	0.07	0.10	0.08	0.07	0.06	0.05
SC	0.04	0.02	0.06	0.02	0.00	0.03	0.03	0.02	0.00	0.04	0.03	0.03	0.04	0.05	0.06	0.04	0.07	0.05	0.07	0.06	0.07	0.07	0.07	0.08	0.09	0.08	0.08	0.08	0.10
SD	0.14	0.06	0.00	0.00	0.00	0.06	0.00	0.11	0.03	0.09	0.26	0.05	0.07	0.10	0.08	0.06	0.00	0.06	0.11	0.06	0.04	0.08	0.09	0.06	0.04	0.04	0.00	0.03	0.03
TN	0.08	0.03	0.04	0.02	0.04	0.07	0.03	0.06	0.04	0.05	0.06	0.06	0.08	0.05	0.07	0.06	0.05	0.07	0.05	0.09	0.07	0.09	0.07	0.07	0.08	0.08	0.08	0.09	0.08
TX	0.03	0.03	0.03	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.04	0.06	0.05	0.05	0.05	0.06	0.06	0.06	0.07	0.07	0.06	0.07	0.07	0.07	0.08	0.08	0.07	0.08	0.08
UT	0.04	0.03	0.02	0.07	0.05	0.07	0.03	0.03	0.04	0.05	0.05	0.05	0.07	0.06	0.05	0.05	0.08	0.08	0.08	0.08	0.07	0.07	0.08	0.08	0.08	0.07	0.07	0.07	0.07
VA	0.02	0.03	0.02	0.02	0.02	0.04	0.04	0.03	0.04	0.05	0.07	0.09	0.10	0.08	0.10	0.09	0.10	0.08	0.07	0.08	0.09	0.07	0.07	0.06	0.09	0.08	0.07	0.08	0.10
VT	0.04	0.08	0.08	0.00	0.04	0.00	0.02	0.02	0.00	0.04	0.04	0.04	0.06	0.05	0.03	0.04	0.04	0.00	0.05	0.06	0.04	0.01	0.07	0.06	0.10	0.07	0.11	0.05	0.04
WA	0.04	0.02	0.02	0.02	0.03	0.03	0.02	0.04	0.04	0.04	0.04	0.05	0.06	0.06	0.06	0.07	0.08	0.09	0.08	0.09	0.10	0.09	0.09	0.09	0.08	0.09	0.10	0.10	0.10
WI	0.03	0.03	0.02	0.02	0.02	0.03	0.04	0.05	0.06	0.06	0.06	0.07	0.05	0.06	0.07	0.08	0.08	0.10	0.11	0.10	0.11	0.14	0.11	0.13	0.12	0.12	0.12	0.12	0.11
WV	0.00	0.04	0.05	0.08	0.07	0.11	0.02	0.02	0.00	0.02	0.09	0.01	0.04	0.02	0.05	0.07	0.02	0.06	0.03	0.03	0.04	0.04	0.04	0.05	0.06	0.03	0.00	0.04	0.06
WY	0.06	0.00	0.00	0.00	0.07	0.05	0.00	0.00	0.00	0.12	0.00	0.06	0.06	0.00	0.00	0.00	0.13	0.05	0.05	0.10	0.00	0.10	0.03	0.05	0.09	0.05	0.05	0.09	0.02

Note: Table 9.4 summarizes the share of female inventors from the USPTO dataset consisting of patents granted in years 1980-2008, including all 50 states and DC. In years 1980, 1982 and 1985, there were no patents granted for neither women nor men in Alaska. Source: Authors' rendering of USPTO data (2026).

Table 9.5: The female share of bachelor's degree holders who have studied STEM by cohort and state.

State	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
AK	0.43	0.33	0.47	0.41	0.25	0.37	0.30	0.50	0.38	0.42	0.49	0.43	0.44	0.55	0.34	0.42	0.45	0.35	0.52	0.38	0.43	0.38	0.46	0.55	0.55	0.53	0.60	0.56	0.51
AL	0.46	0.47	0.50	0.48	0.46	0.47	0.44	0.45	0.44	0.47	0.54	0.52	0.50	0.49	0.51	0.54	0.56	0.52	0.46	0.47	0.51	0.50	0.52	0.54	0.54	0.48	0.51	0.50	0.51
AR	0.46	0.51	0.49	0.43	0.52	0.42	0.50	0.45	0.46	0.56	0.53	0.48	0.50	0.48	0.50	0.52	0.50	0.53	0.55	0.52	0.49	0.57	0.58	0.52	0.49	0.54	0.54	0.58	0.56
AZ	0.39	0.41	0.43	0.42	0.33	0.43	0.41	0.43	0.37	0.42	0.45	0.42	0.42	0.47	0.43	0.49	0.43	0.44	0.45	0.47	0.48	0.47	0.49	0.44	0.49	0.49	0.46	0.47	0.49
CA	0.42	0.39	0.40	0.41	0.42	0.39	0.40	0.39	0.41	0.42	0.42	0.43	0.43	0.46	0.44	0.45	0.44	0.46	0.45	0.43	0.47	0.46	0.45	0.45	0.45	0.45	0.46	0.46	0.48
CO	0.39	0.40	0.42	0.36	0.43	0.41	0.38	0.40	0.37	0.43	0.41	0.39	0.41	0.45	0.44	0.45	0.49	0.48	0.51	0.43	0.47	0.43	0.47	0.45	0.50	0.49	0.48	0.45	0.45
CT	0.48	0.42	0.44	0.46	0.46	0.43	0.42	0.47	0.43	0.49	0.48	0.42	0.47	0.48	0.50	0.49	0.49	0.48	0.46	0.46	0.46	0.44	0.48	0.47	0.43	0.48	0.49	0.47	0.53
DC	0.42	0.43	0.42	0.44	0.42	0.44	0.40	0.44	0.41	0.47	0.47	0.46	0.50	0.49	0.45	0.47	0.48	0.44	0.48	0.53	0.48	0.43	0.55	0.51	0.45	0.43	0.47	0.46	0.50
DE	0.38	0.52	0.59	0.53	0.41	0.39	0.47	0.49	0.44	0.52	0.52	0.49	0.51	0.49	0.46	0.42	0.42	0.50	0.40	0.39	0.55	0.42	0.51	0.46	0.48	0.53	0.50	0.46	0.41
FL	0.44	0.45	0.43	0.45	0.45	0.43	0.41	0.46	0.42	0.46	0.47	0.49	0.49	0.52	0.49	0.51	0.50	0.51	0.49	0.47	0.50	0.48	0.50	0.51	0.52	0.50	0.50	0.51	0.52
GA	0.44	0.40	0.42	0.46	0.46	0.49	0.46	0.45	0.50	0.48	0.49	0.52	0.52	0.51	0.55	0.53	0.49	0.52	0.51	0.50	0.56	0.51	0.52	0.52	0.49	0.48	0.55	0.51	0.51
HI	0.42	0.42	0.42	0.41	0.45	0.47	0.44	0.43	0.44	0.40	0.44	0.46	0.41	0.51	0.44	0.44	0.48	0.47	0.52	0.48	0.47	0.44	0.49	0.52	0.43	0.57	0.51	0.57	0.56
IA	0.46	0.43	0.46	0.44	0.42	0.47	0.40	0.43	0.41	0.45	0.43	0.47	0.48	0.45	0.50	0.49	0.45	0.47	0.47	0.48	0.50	0.49	0.52	0.52	0.52	0.46	0.47	0.47	0.51
ID	0.43	0.40	0.41	0.41	0.34	0.45	0.34	0.33	0.39	0.46	0.39	0.39	0.42	0.49	0.46	0.43	0.38	0.36	0.43	0.40	0.47	0.46	0.41	0.41	0.49	0.44	0.39	0.50	0.54
IL	0.44	0.43	0.44	0.43	0.42	0.42	0.41	0.43	0.45	0.43	0.44	0.48	0.48	0.49	0.49	0.48	0.47	0.47	0.45	0.49	0.47	0.46	0.48	0.48	0.49	0.46	0.50	0.51	0.50
IN	0.41	0.41	0.42	0.45	0.42	0.42	0.46	0.44	0.45	0.47	0.46	0.46	0.47	0.49	0.48	0.51	0.47	0.43	0.50	0.48	0.49	0.49	0.47	0.51	0.50	0.48	0.53	0.51	0.48
KS	0.41	0.44	0.44	0.44	0.41	0.47	0.43	0.45	0.44	0.42	0.46	0.47	0.45	0.45	0.51	0.48	0.48	0.48	0.52	0.51	0.48	0.48	0.49	0.48	0.50	0.49	0.50	0.43	0.53
KY	0.50	0.48	0.49	0.48	0.48	0.46	0.45	0.54	0.51	0.50	0.49	0.51	0.53	0.49	0.53	0.47	0.48	0.51	0.53	0.53	0.53	0.50	0.53	0.51	0.52	0.50	0.52	0.56	0.53
LA	0.47	0.45	0.45	0.51	0.40	0.49	0.46	0.52	0.52	0.51	0.52	0.52	0.49	0.47	0.55	0.49	0.52	0.55	0.58	0.48	0.52	0.50	0.55	0.51	0.52	0.52	0.52	0.56	0.46
MA	0.45	0.43	0.44	0.46	0.46	0.43	0.45	0.43	0.42	0.47	0.46	0.45	0.48	0.48	0.51	0.49	0.52	0.48	0.49	0.48	0.49	0.51	0.50	0.49	0.48	0.54	0.48	0.51	0.49
MD	0.50	0.46	0.48	0.47	0.47	0.49	0.44	0.44	0.48	0.46	0.47	0.44	0.47	0.49	0.50	0.50	0.50	0.51	0.52	0.49	0.49	0.47	0.48	0.48	0.48	0.50	0.48	0.47	0.48
ME	0.40	0.43	0.45	0.46	0.46	0.49	0.50	0.49	0.47	0.51	0.49	0.41	0.47	0.43	0.49	0.49	0.48	0.50	0.43	0.52	0.47	0.45	0.52	0.55	0.49	0.51	0.53	0.52	0.58
MI	0.43	0.43	0.43	0.45	0.41	0.41	0.42	0.42	0.44	0.44	0.45	0.45	0.46	0.49	0.47	0.47	0.47	0.47	0.46	0.47	0.46	0.46	0.46	0.46	0.47	0.51	0.50	0.51	0.49
MN	0.44	0.43	0.45	0.42	0.42	0.39	0.42	0.39	0.46	0.47	0.47	0.46	0.45	0.47	0.49	0.49	0.47	0.46	0.46	0.49	0.47	0.49	0.48	0.49	0.48	0.51	0.51	0.53	0.51
MO	0.46	0.44	0.43	0.43	0.46	0.46	0.41	0.42	0.47	0.46	0.48	0.45	0.50	0.47	0.48	0.48	0.47	0.47	0.48	0.48	0.47	0.49	0.50	0.51	0.52	0.51	0.49	0.54	0.51
MS	0.44	0.49	0.46	0.46	0.56	0.48	0.51	0.52	0.53	0.48	0.57	0.55	0.55	0.51	0.57	0.58	0.57	0.58	0.55	0.60	0.60	0.53	0.52	0.52	0.55	0.59	0.52	0.57	0.55
MT	0.36	0.32	0.42	0.40	0.35	0.38	0.31	0.38	0.43	0.43	0.45	0.38	0.44	0.40	0.46	0.49	0.45	0.50	0.45	0.42	0.52	0.45	0.46	0.51	0.41	0.43	0.59	0.56	0.46
NC	0.48	0.46	0.49	0.47	0.47	0.50	0.47	0.43	0.49	0.48	0.51	0.51	0.51	0.49	0.52	0.54	0.51	0.52	0.52	0.51	0.53	0.50	0.51	0.51	0.54	0.52	0.54	0.53	0.48
ND	0.43	0.47	0.43	0.48	0.42	0.48	0.37	0.52	0.47	0.50	0.44	0.47	0.50	0.46	0.52	0.51	0.51	0.46	0.56	0.46	0.55	0.52	0.38	0.53	0.57	0.48	0.54	0.59	0.57
NE	0.42	0.42	0.50	0.40	0.45	0.44	0.41	0.45	0.41	0.46	0.49	0.49	0.50	0.48	0.48	0.45	0.48	0.54	0.49	0.54	0.50	0.47	0.50	0.53	0.58	0.52	0.53	0.53	0.55
NH	0.47	0.51	0.47	0.43	0.48	0.46	0.44	0.35	0.43	0.41	0.46	0.46	0.47	0.41	0.45	0.48	0.47	0.50	0.47	0.37	0.42	0.48	0.51	0.45	0.42	0.48	0.51	0.55	0.44
NJ	0.44	0.41	0.43	0.42	0.41	0.43	0.40	0.40	0.44	0.43	0.44	0.47	0.46	0.45	0.47	0.50	0.46	0.47	0.45	0.46	0.46	0.45	0.43	0.46	0.47	0.48	0.46	0.50	0.50
NM	0.39	0.38	0.43	0.40	0.36	0.41	0.45	0.44	0.39	0.47	0.37	0.43	0.39	0.46	0.54	0.43	0.47	0.51	0.49	0.49	0.45	0.52	0.44	0.51	0.55	0.50	0.52	0.48	0.53
NV	0.39	0.52	0.39	0.43	0.39	0.42	0.38	0.46	0.49	0.44	0.42	0.44	0.48	0.45	0.43	0.49	0.46	0.33	0.52	0.39	0.37	0.43	0.47	0.46	0.53	0.43	0.47	0.53	0.51
NY	0.43	0.42	0.43	0.44	0.43	0.42	0.43	0.43	0.43	0.43	0.45	0.48	0.46	0.46	0.48	0.48	0.47	0.47	0.45	0.47	0.47	0.48	0.47	0.49	0.49	0.49	0.48	0.48	0.49
OH	0.43	0.44	0.45	0.45	0.44	0.44	0.41	0.43	0.47	0.46	0.45	0.47	0.48	0.48	0.48	0.52	0.50	0.48	0.50	0.47	0.46	0.50	0.51	0.49	0.50	0.51	0.51	0.51	0.51
OK	0.38	0.42	0.40	0.42	0.44	0.45	0.49	0.42	0.48	0.44	0.44	0.50	0.47	0.47	0.48	0.47	0.50	0.52	0.43	0.45	0.49	0.51	0.47	0.50	0.48	0.50	0.51	0.44	0.53
OR	0.37	0.41	0.35	0.42	0.37	0.38	0.42	0.33	0.40	0.40	0.40	0.39	0.42	0.39	0.45	0.43	0.49	0.45	0.47	0.43	0.48	0.49	0.50	0.43	0.48	0.53	0.44	0.47	0.48
PA	0.44	0.44	0.44	0.48	0.47	0.43	0.44	0.43	0.44	0.45	0.46	0.46	0.48	0.48	0.48	0.51	0.49	0.47	0.47	0.45	0.46	0.48	0.48	0.47	0.51	0.50	0.47	0.48	0.50
RI	0.42	0.41	0.37	0.49	0.44	0.46	0.39	0.43	0.48	0.39	0.49	0.44	0.60	0.50	0.43	0.47	0.50	0.54	0.54	0.45	0.46	0.47	0.47	0.48	0.49	0.49	0.49	0.51	0.54
SC	0.46	0.46	0.45	0.47	0.51	0.48	0.52	0.44	0.53	0.50	0.48	0.48	0.53	0.50	0.50	0.56	0.50	0.51	0.49	0.54	0.53	0.51	0.49	0.51	0.50	0.53	0.52	0.50	0.48
SD	0.46	0.52	0.42	0.38	0.45	0.45	0.46	0.41	0.44	0.49	0.47	0.52	0.45	0.45	0.52	0.50	0.58	0.45	0.47	0.45	0.48	0.53	0.49	0.54	0.45	0.51	0.48	0.53	0.56
TN	0.46	0.49	0.48	0.48	0.52	0.45	0.45	0.46	0.44	0.53	0.50	0.52	0.50	0.45	0.53	0.51	0.51	0.52	0.52	0.50	0.47	0.52	0.49	0.56	0.52	0.53	0.52	0.51	0.53
TX	0.43	0.39	0.42	0.41	0.43	0.41	0.42	0.43	0.42	0.43	0.42	0.45	0.45	0.48	0.48	0.48	0.47	0.45	0.46	0.48	0.46	0.48	0.45	0.48	0.49	0.46	0.45	0.48	0.48
UT	0.30	0.33	0.38	0.29	0.31	0.38	0.37	0.33	0.32	0.37	0.34	0.37	0.36	0.37	0.36	0.35	0.38	0.33	0.38	0.37	0.34	0.40	0.35	0.43	0.44	0.42	0.38	0.46	0.44
VA	0.48	0.43	0.48	0.49	0.46	0.43	0.42	0.46	0.45	0.45	0.45	0.45	0.49	0.47	0.53	0.46	0.47	0.46	0.46	0.52	0.51	0.46	0.48	0.45	0.51	0.49	0.49	0.48	0.49
VT	0.49	0.50	0.45	0.42	0.32	0.43	0.46	0.38	0.41	0.42	0.46	0.42	0.48	0.47	0.44	0.43	0.53	0.53	0.48	0.50	0.47	0.43	0.44	0.46	0.51	0.42	0.49	0.51	0.55
WA	0.39	0.41	0.41	0.37	0.35	0.39	0.40	0.39	0.42	0.42	0.42	0.46	0.43	0.48	0.48	0.45	0.43	0.44	0.44	0.48	0.42	0.45	0.48	0.48	0.45	0.44	0.45	0.48	0.47
WI	0.45	0.43	0.44	0.40	0.50	0.41	0.40	0.43	0.43	0.43	0.45	0.46	0.46	0.47	0.51	0.50	0.50	0.48	0.50	0.48	0.51	0.47	0.51	0.49	0.50	0.50	0.52	0.52	0.49
WV	0.46	0.48	0.50	0.48	0.44	0.45	0.46	0.50	0.39	0.46	0.52	0.49	0.46	0.47	0.45	0.50	0.49	0.56	0.52	0.45	0.51	0.53	0.54	0.53	0.47	0.55	0.52	0.43	0.55
WY	0.28	0.40	0.42	0.34	0.44	0.40	0.33	0.29	0.44	0.39	0.43	0.43	0.41	0.30	0.48	0.42	0.46	0.52	0.51	0.48	0.45	0.47	0.49	0.49	0.45	0.48	0.51	0.44	0.43

Note: Table 9.5 summarizes the female share of bachelor's degree holders who have studied STEM in the cohorts 1980-2008, including all 50 states and DC. Source: Authors' rendering of IPUMS USA data (2025).

Table 9.6: The female share of bachelor's degree holders who studied math-intensive STEM by cohort and state.

State	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
AK	0.20	0.16	0.26	0.28	0.11	0.18	0.14	0.36	0.15	0.20	0.26	0.17	0.25	0.33	0.13	0.28	0.24	0.21	0.45	0.22	0.21	0.16	0.23	0.26	0.25	0.27	0.41	0.44	0.37
AL	0.22	0.29	0.29	0.28	0.30	0.29	0.29	0.28	0.25	0.27	0.33	0.32	0.30	0.30	0.29	0.28	0.31	0.34	0.25	0.22	0.31	0.27	0.33	0.38	0.27	0.24	0.25	0.24	0.29
AR	0.22	0.25	0.34	0.22	0.25	0.21	0.27	0.22	0.23	0.35	0.33	0.28	0.32	0.24	0.26	0.25	0.25	0.31	0.27	0.30	0.30	0.28	0.29	0.24	0.20	0.27	0.28	0.26	0.33
AZ	0.20	0.24	0.22	0.21	0.17	0.24	0.21	0.25	0.20	0.20	0.22	0.19	0.19	0.26	0.22	0.30	0.27	0.22	0.28	0.26	0.25	0.29	0.25	0.22	0.25	0.22	0.22	0.28	0.26
CA	0.24	0.22	0.23	0.24	0.24	0.20	0.22	0.20	0.23	0.24	0.22	0.24	0.24	0.25	0.23	0.25	0.24	0.26	0.26	0.23	0.26	0.23	0.25	0.23	0.25	0.24	0.26	0.25	0.27
CO	0.22	0.23	0.28	0.22	0.27	0.27	0.23	0.22	0.20	0.25	0.24	0.22	0.20	0.26	0.25	0.24	0.32	0.32	0.30	0.24	0.22	0.20	0.26	0.28	0.26	0.26	0.25	0.27	0.25
CT	0.24	0.24	0.24	0.28	0.24	0.24	0.26	0.25	0.21	0.28	0.29	0.23	0.27	0.25	0.26	0.22	0.26	0.24	0.29	0.27	0.26	0.24	0.25	0.25	0.20	0.27	0.24	0.23	0.33
DC	0.27	0.32	0.29	0.33	0.26	0.31	0.24	0.29	0.28	0.30	0.29	0.32	0.38	0.32	0.33	0.31	0.28	0.28	0.21	0.37	0.36	0.26	0.33	0.28	0.29	0.23	0.30	0.25	0.31
DE	0.21	0.30	0.41	0.31	0.23	0.18	0.35	0.29	0.21	0.22	0.33	0.18	0.26	0.36	0.28	0.24	0.28	0.18	0.25	0.29	0.33	0.20	0.29	0.26	0.23	0.25	0.25	0.18	0.19
FL	0.24	0.27	0.30	0.27	0.29	0.26	0.22	0.23	0.22	0.26	0.23	0.26	0.28	0.29	0.30	0.31	0.25	0.27	0.28	0.25	0.26	0.24	0.26	0.24	0.26	0.25	0.22	0.23	0.27
GA	0.25	0.23	0.26	0.31	0.27	0.28	0.27	0.29	0.34	0.29	0.26	0.33	0.32	0.30	0.31	0.34	0.27	0.28	0.29	0.28	0.32	0.26	0.26	0.25	0.25	0.26	0.31	0.28	0.27
HI	0.23	0.34	0.31	0.26	0.28	0.27	0.31	0.25	0.25	0.23	0.22	0.26	0.25	0.27	0.21	0.24	0.33	0.25	0.34	0.22	0.27	0.24	0.21	0.17	0.22	0.33	0.25	0.35	0.25
IA	0.21	0.22	0.26	0.20	0.21	0.25	0.18	0.21	0.22	0.19	0.20	0.22	0.25	0.18	0.26	0.22	0.18	0.22	0.23	0.20	0.27	0.22	0.23	0.20	0.19	0.18	0.18	0.19	0.27
ID	0.23	0.22	0.23	0.22	0.21	0.22	0.16	0.22	0.15	0.27	0.23	0.18	0.20	0.29	0.26	0.17	0.17	0.23	0.22	0.20	0.21	0.24	0.18	0.10	0.28	0.16	0.17	0.20	0.28
IL	0.23	0.24	0.25	0.25	0.24	0.22	0.21	0.24	0.27	0.23	0.26	0.25	0.26	0.26	0.28	0.28	0.27	0.24	0.24	0.28	0.24	0.22	0.24	0.23	0.24	0.24	0.25	0.28	0.26
IN	0.20	0.23	0.22	0.24	0.20	0.22	0.21	0.21	0.25	0.22	0.21	0.24	0.22	0.25	0.23	0.26	0.24	0.23	0.30	0.23	0.26	0.26	0.19	0.23	0.25	0.20	0.25	0.24	0.18
KS	0.24	0.21	0.21	0.24	0.22	0.30	0.17	0.23	0.22	0.16	0.24	0.29	0.25	0.21	0.19	0.20	0.25	0.24	0.26	0.27	0.20	0.18	0.23	0.19	0.21	0.24	0.22	0.16	0.26
KY	0.28	0.26	0.27	0.27	0.27	0.26	0.21	0.25	0.28	0.25	0.24	0.23	0.25	0.24	0.27	0.19	0.22	0.21	0.29	0.27	0.29	0.21	0.27	0.24	0.24	0.23	0.24	0.34	0.25
LA	0.22	0.27	0.28	0.35	0.25	0.25	0.23	0.33	0.27	0.30	0.27	0.27	0.25	0.28	0.32	0.27	0.30	0.31	0.36	0.25	0.29	0.26	0.27	0.29	0.29	0.31	0.28	0.31	0.24
MA	0.24	0.24	0.25	0.28	0.26	0.23	0.25	0.23	0.21	0.25	0.25	0.24	0.26	0.23	0.27	0.27	0.32	0.26	0.27	0.24	0.26	0.28	0.26	0.28	0.25	0.26	0.24	0.27	0.26
MD	0.32	0.26	0.29	0.28	0.30	0.32	0.30	0.29	0.31	0.27	0.30	0.25	0.29	0.31	0.29	0.27	0.31	0.31	0.30	0.29	0.28	0.27	0.24	0.27	0.25	0.28	0.24	0.27	0.28
ME	0.17	0.21	0.18	0.26	0.15	0.27	0.22	0.29	0.20	0.26	0.20	0.14	0.23	0.17	0.26	0.27	0.26	0.17	0.12	0.23	0.23	0.21	0.20	0.33	0.18	0.28	0.11	0.15	0.15
MI	0.24	0.25	0.27	0.26	0.26	0.23	0.26	0.25	0.25	0.27	0.27	0.27	0.27	0.28	0.26	0.26	0.30	0.26	0.27	0.26	0.24	0.24	0.26	0.24	0.21	0.27	0.23	0.27	0.25
MN	0.24	0.20	0.23	0.26	0.22	0.21	0.21	0.17	0.26	0.24	0.24	0.24	0.22	0.28	0.23	0.24	0.25	0.24	0.20	0.23	0.20	0.21	0.22	0.23	0.22	0.24	0.26	0.27	0.24
MO	0.22	0.21	0.24	0.22	0.26	0.27	0.22	0.24	0.25	0.22	0.30	0.22	0.28	0.23	0.25	0.22	0.27	0.24	0.23	0.23	0.23	0.24	0.25	0.26	0.29	0.25	0.26	0.25	0.26
MS	0.24	0.27	0.30	0.23	0.40	0.34	0.37	0.26	0.21	0.30	0.38	0.26	0.36	0.24	0.30	0.39	0.34	0.23	0.35	0.31	0.35	0.29	0.25	0.26	0.33	0.26	0.21	0.27	0.30
MT	0.19	0.19	0.21	0.14	0.24	0.16	0.23	0.17	0.24	0.24	0.22	0.26	0.27	0.26	0.23	0.29	0.22	0.30	0.19	0.14	0.23	0.23	0.15	0.21	0.17	0.19	0.37	0.22	0.34
NC	0.26	0.28	0.31	0.26	0.27	0.30	0.24	0.26	0.32	0.30	0.27	0.30	0.29	0.29	0.29	0.34	0.30	0.28	0.27	0.26	0.29	0.25	0.25	0.25	0.26	0.23	0.29	0.30	0.23
ND	0.17	0.31	0.20	0.23	0.16	0.18	0.07	0.21	0.18	0.23	0.16	0.18	0.22	0.20	0.23	0.18	0.22	0.19	0.27	0.16	0.24	0.27	0.10	0.30	0.34	0.19	0.29	0.32	0.32
NE	0.18	0.18	0.23	0.22	0.24	0.26	0.22	0.26	0.17	0.18	0.25	0.23	0.19	0.22	0.20	0.17	0.24	0.28	0.22	0.21	0.22	0.25	0.22	0.24	0.25	0.21	0.22	0.28	0.31
NH	0.30	0.30	0.28	0.23	0.28	0.17	0.18	0.21	0.27	0.21	0.18	0.26	0.26	0.20	0.29	0.22	0.29	0.25	0.27	0.16	0.18	0.22	0.21	0.22	0.18	0.22	0.29	0.30	0.22
NJ	0.29	0.23	0.29	0.26	0.26	0.26	0.23	0.23	0.27	0.24	0.26	0.27	0.26	0.25	0.27	0.31	0.26	0.26	0.26	0.29	0.26	0.26	0.24	0.26	0.26	0.25	0.23	0.29	0.29
NM	0.27	0.30	0.25	0.26	0.20	0.24	0.32	0.21	0.13	0.32	0.18	0.28	0.28	0.30	0.36	0.27	0.26	0.30	0.25	0.27	0.21	0.33	0.19	0.28	0.28	0.26	0.22	0.27	0.35
NV	0.18	0.32	0.26	0.24	0.23	0.21	0.29	0.28	0.30	0.19	0.15	0.14	0.30	0.29	0.29	0.33	0.21	0.18	0.32	0.12	0.18	0.14	0.21	0.16	0.27	0.25	0.27	0.36	0.27
NY	0.25	0.26	0.27	0.28	0.27	0.24	0.28	0.26	0.24	0.25	0.26	0.26	0.25	0.27	0.29	0.26	0.27	0.27	0.25	0.26	0.26	0.26	0.24	0.29	0.28	0.26	0.27	0.25	0.27
OH	0.24	0.24	0.26	0.24	0.24	0.25	0.19	0.22	0.24	0.22	0.24	0.26	0.27	0.26	0.24	0.27	0.26	0.23	0.26	0.24	0.21	0.26	0.23	0.24	0.25	0.24	0.25	0.22	0.27
OK	0.22	0.25	0.24	0.25	0.24	0.36	0.26	0.25	0.21	0.27	0.29	0.26	0.19	0.21	0.26	0.24	0.22	0.35	0.24	0.22	0.25	0.25	0.25	0.24	0.24	0.24	0.33	0.22	0.25
OR	0.19	0.25	0.24	0.19	0.18	0.19	0.21	0.18	0.18	0.28	0.17	0.23	0.21	0.19	0.17	0.20	0.23	0.25	0.28	0.26	0.23	0.25	0.28	0.17	0.19	0.32	0.15	0.22	0.22
PA	0.24	0.25	0.25	0.27	0.27	0.22	0.27	0.23	0.22	0.25	0.24	0.24	0.26	0.27	0.27	0.29	0.26	0.24	0.27	0.23	0.25	0.24	0.23	0.25	0.27	0.25	0.24	0.25	0.24
RI	0.26	0.23	0.22	0.26	0.30	0.25	0.23	0.19	0.32	0.24	0.31	0.22	0.31	0.26	0.19	0.22	0.27	0.28	0.27	0.26	0.27	0.22	0.29	0.24	0.25	0.25	0.30	0.36	0.33
SC	0.25	0.29	0.29	0.28	0.31	0.27	0.35	0.25	0.35	0.30	0.27	0.31	0.32	0.32	0.31	0.33	0.27	0.28	0.25	0.32	0.26	0.29	0.26	0.29	0.24	0.30	0.28	0.20	0.26
SD	0.19	0.32	0.25	0.22	0.19	0.28	0.25	0.13	0.24	0.27	0.26	0.24	0.25	0.13	0.26	0.19	0.32	0.23	0.22	0.22	0.24	0.26	0.18	0.29	0.17	0.24	0.10	0.22	0.36
TN	0.27	0.28	0.27	0.24	0.27	0.26	0.21	0.19	0.24	0.29	0.27	0.30	0.31	0.24	0.22	0.30	0.31	0.26	0.26	0.24	0.24	0.24	0.20	0.33	0.27	0.25	0.26	0.26	0.27
TX	0.29	0.23	0.24	0.26	0.26	0.22	0.24	0.26	0.24	0.24	0.23	0.23	0.27	0.29	0.28	0.28	0.27	0.27	0.27	0.29	0.26	0.26	0.26	0.27	0.30	0.24	0.23	0.28	0.26
UT	0.16	0.19	0.27	0.18	0.17	0.18	0.20	0.16	0.14	0.16	0.13	0.18	0.16	0.20	0.17	0.14	0.16	0.14	0.13	0.17	0.15	0.19	0.15	0.16	0.17	0.16	0.15	0.22	0.21
VA	0.29	0.25	0.29	0.28	0.26	0.25	0.28	0.28	0.25	0.26	0.26	0.29	0.27	0.27	0.30	0.24	0.25	0.25	0.23	0.31	0.28	0.23	0.26	0.24	0.28	0.26	0.30	0.24	0.26
VT	0.29	0.38	0.14	0.25	0.18	0.23	0.31	0.11	0.22	0.19	0.24	0.26	0.28	0.20	0.17	0.24	0.33	0.25	0.24	0.32	0.29	0.20	0.22	0.21	0.19	0.20	0.19	0.21	0.32
WA	0.24	0.20	0.24	0.20	0.22	0.24	0.21	0.22	0.24	0.25	0.26	0.24	0.24	0.24	0.29	0.23	0.25	0.22	0.25	0.24	0.23	0.24	0.28	0.23	0.21	0.19	0.23	0.28	0.27
WI	0.23	0.23	0.19	0.21	0.28	0.20	0.17	0.21	0.19	0.20	0.24	0.24	0.26	0.23	0.24	0.24	0.25	0.25	0.24	0.20	0.26	0.22	0.20	0.25	0.22	0.24	0.25	0.25	0.23
WV	0.25	0.27	0.24	0.24	0.22	0.24	0.22	0.24	0.15	0.25	0.20	0.22	0.22	0.21	0.22	0.27	0.28	0.30	0.27	0.18	0.26	0.24	0.21	0.28	0.21	0.23	0.16	0.12	0.28
WY	0.10	0.21	0.13	0.15	0.23	0.21	0.12	0.18	0.20	0.13	0.13	0.24	0.26	0.13	0.26	0.16	0.24	0.37	0.25	0.36	0.27	0.23	0.22	0.22	0.17	0.24	0.23	0.22	0.13

Note: Table 9.6 summarizes the female share of bachelor's degree holders who have studied math-intensive STEM in the cohorts 1980-2008, including all 50 states and DC.
Source: Authors' rendering of IPUMS USA data (2025).

Table 9.7: Summary statistics for the share of female inventors.

Year	Min	Q1	Median	Mean	Q3	Max
1980	0.00	0.02	0.02	0.03	0.04	0.14
1981	0.00	0.02	0.03	0.03	0.03	0.11
1982	0.00	0.01	0.03	0.03	0.04	0.17
1983	0.00	0.02	0.03	0.04	0.04	0.21
1984	0.00	0.02	0.04	0.03	0.04	0.11
1985	0.00	0.03	0.03	0.04	0.05	0.11
1986	0.00	0.02	0.03	0.03	0.05	0.10
1987	0.00	0.03	0.04	0.04	0.05	0.12
1988	0.00	0.02	0.04	0.04	0.05	0.12
1989	0.00	0.04	0.05	0.05	0.06	0.16
1990	0.00	0.04	0.05	0.06	0.06	0.26
1991	0.00	0.04	0.05	0.05	0.06	0.09
1992	0.00	0.04	0.06	0.05	0.07	0.10
1993	0.00	0.04	0.06	0.06	0.07	0.15
1994	0.00	0.05	0.06	0.06	0.07	0.10
1995	0.00	0.05	0.06	0.06	0.07	0.10
1996	0.00	0.05	0.07	0.06	0.08	0.13
1997	0.00	0.05	0.07	0.07	0.08	0.23
1998	0.00	0.05	0.07	0.07	0.08	0.11
1999	0.00	0.06	0.08	0.07	0.09	0.11
2000	0.00	0.06	0.07	0.08	0.10	0.16
2001	0.00	0.06	0.08	0.08	0.09	0.14
2002	0.02	0.06	0.08	0.08	0.10	0.17
2003	0.00	0.07	0.08	0.08	0.10	0.15
2004	0.04	0.08	0.09	0.09	0.10	0.13
2005	0.03	0.08	0.08	0.09	0.11	0.24
2006	0.00	0.07	0.08	0.08	0.11	0.15
2007	0.03	0.07	0.08	0.09	0.10	0.15
2008	0.02	0.07	0.09	0.09	0.10	0.14

Note: Table 9.7 summarizes the share of female inventors for patents granted in years 1980-2008, including all 50 states and DC. The mean reflects the unweighted state-level average. Source: Authors' rendering of USPTO data (2026).

Table 9.8: Summary statistics for the female share of bachelor's degree holders who have studied STEM.

Year	Lower_Fence	Min	Q1	Median	Mean	Q3	Max	Upper_Fence
1980	0.33	0.28	0.41	0.43	0.43	0.46	0.50	0.54
1981	0.33	0.32	0.41	0.43	0.43	0.46	0.52	0.54
1982	0.36	0.35	0.42	0.44	0.44	0.46	0.59	0.52
1983	0.33	0.29	0.41	0.44	0.44	0.46	0.53	0.55
1984	0.33	0.25	0.41	0.44	0.43	0.46	0.56	0.54
1985	0.33	0.37	0.41	0.43	0.44	0.46	0.50	0.54
1986	0.32	0.30	0.40	0.42	0.42	0.46	0.52	0.54
1987	0.35	0.29	0.42	0.43	0.43	0.46	0.54	0.52
1988	0.33	0.32	0.42	0.44	0.44	0.47	0.53	0.55
1989	0.36	0.37	0.43	0.46	0.45	0.48	0.56	0.54
1990	0.36	0.34	0.44	0.46	0.46	0.49	0.57	0.56
1991	0.36	0.37	0.44	0.46	0.46	0.48	0.55	0.56
1992	0.38	0.36	0.45	0.47	0.47	0.50	0.60	0.58
1993	0.40	0.30	0.46	0.47	0.47	0.49	0.55	0.54
1994	0.37	0.34	0.46	0.48	0.48	0.51	0.57	0.59
1995	0.39	0.35	0.46	0.49	0.48	0.50	0.58	0.57
1996	0.42	0.38	0.47	0.48	0.48	0.50	0.58	0.54
1997	0.38	0.33	0.46	0.48	0.48	0.52	0.58	0.60
1998	0.37	0.38	0.46	0.48	0.48	0.52	0.58	0.61
1999	0.38	0.37	0.45	0.48	0.47	0.50	0.60	0.56
2000	0.39	0.34	0.46	0.48	0.48	0.50	0.60	0.57
2001	0.39	0.38	0.46	0.48	0.48	0.50	0.57	0.57
2002	0.41	0.35	0.47	0.49	0.49	0.51	0.58	0.57
2003	0.39	0.41	0.46	0.49	0.49	0.52	0.56	0.59
2004	0.41	0.41	0.48	0.49	0.49	0.52	0.58	0.59
2005	0.43	0.42	0.48	0.50	0.49	0.52	0.59	0.57
2006	0.42	0.38	0.48	0.50	0.50	0.52	0.60	0.58
2007	0.38	0.43	0.47	0.51	0.50	0.53	0.59	0.62
2008	0.40	0.41	0.48	0.51	0.50	0.53	0.58	0.61

Note: Table 9.8 summarizes the female share of bachelor's degree holders for cohorts 1980-2008, including all 50 states and DC. The mean reflects the unweighted state-level average. Source: Authors' rendering of IPUMS USA data (2025).

Table 9.9: Summary statistics for the female share of bachelor's degree holders who have studied math-intensive STEM.

Year	Lower_Fence	Min	Q1	Median	Mean	Q3	Max	Upper_Fence
1980	0.15	0.10	0.21	0.24	0.23	0.25	0.32	0.31
1981	0.15	0.16	0.22	0.25	0.25	0.28	0.38	0.35
1982	0.15	0.13	0.23	0.25	0.25	0.28	0.41	0.36
1983	0.14	0.14	0.22	0.25	0.25	0.27	0.35	0.35
1984	0.14	0.11	0.22	0.24	0.24	0.27	0.40	0.35
1985	0.13	0.16	0.22	0.24	0.24	0.27	0.36	0.35
1986	0.12	0.07	0.21	0.23	0.24	0.27	0.37	0.36
1987	0.13	0.11	0.21	0.23	0.23	0.26	0.36	0.34
1988	0.13	0.13	0.21	0.24	0.23	0.26	0.35	0.33
1989	0.14	0.13	0.22	0.25	0.24	0.27	0.35	0.35
1990	0.14	0.13	0.22	0.24	0.24	0.27	0.38	0.35
1991	0.16	0.14	0.22	0.24	0.24	0.27	0.33	0.34
1992	0.18	0.16	0.24	0.26	0.26	0.28	0.38	0.34
1993	0.13	0.13	0.22	0.26	0.25	0.29	0.36	0.38
1994	0.14	0.13	0.23	0.26	0.26	0.29	0.36	0.38
1995	0.13	0.14	0.22	0.26	0.25	0.28	0.39	0.37
1996	0.17	0.16	0.24	0.26	0.26	0.29	0.34	0.35
1997	0.15	0.14	0.23	0.25	0.26	0.28	0.37	0.36
1998	0.18	0.12	0.24	0.26	0.26	0.28	0.45	0.34
1999	0.14	0.12	0.22	0.24	0.25	0.28	0.37	0.36
2000	0.17	0.15	0.23	0.26	0.25	0.27	0.36	0.33
2001	0.16	0.14	0.22	0.24	0.24	0.26	0.33	0.32
2002	0.13	0.10	0.21	0.24	0.24	0.26	0.33	0.34
2003	0.16	0.10	0.23	0.24	0.25	0.28	0.38	0.34
2004	0.13	0.17	0.21	0.25	0.24	0.26	0.34	0.35
2005	0.18	0.16	0.23	0.24	0.24	0.26	0.33	0.30
2006	0.14	0.10	0.22	0.25	0.24	0.28	0.41	0.36
2007	0.13	0.12	0.22	0.25	0.26	0.28	0.44	0.37
2008	0.19	0.13	0.25	0.26	0.27	0.29	0.37	0.35

Note: Table 9.9 summarizes the female share of bachelor's degree holders who have studied math-intensive STEM for cohorts 1980-2008. The mean reflects the unweighted state-level average. Source: Authors' rendering of IPUMS USA data (2025).

Table 9.10: Annual unemployment rate in the US

Year	Min	Median	Mean	Max
1980	3.8%	6.9%	6.8%	12.2%
1981	3.6%	7.3%	7.3%	12.4%
1982	5.4%	9.0%	9.2%	15.4%
1983	5.2%	9.0%	9.1%	17.1%
1984	4.2%	6.9%	7.3%	14.1%
1985	3.7%	7.0%	7.1%	13.2%
1986	2.6%	6.8%	6.9%	12.4%
1987	2.2%	6.1%	6.2%	11.8%
1988	2.4%	5.2%	5.5%	10.5%
1989	2.5%	4.9%	5.1%	8.7%
1990	2.3%	5.3%	5.4%	8.7%
1991	2.6%	6.5%	6.4%	10.7%
1992	2.8%	6.9%	6.8%	11.2%
1993	2.8%	6.2%	6.3%	10.2%
1994	2.6%	5.5%	5.6%	8.8%
1995	2.6%	5.2%	5.2%	8.6%
1996	2.7%	5.2%	5.1%	8.4%
1997	2.4%	4.8%	4.7%	8.1%
1998	2.5%	4.3%	4.4%	8.3%
1999	2.5%	4.1%	4.1%	6.5%
2000	2.1%	3.8%	3.9%	6.3%
2001	2.8%	4.5%	4.5%	6.4%
2002	3.2%	5.5%	5.4%	7.5%
2003	3.5%	5.6%	5.6%	8.0%
2004	3.3%	5.3%	5.2%	7.5%
2005	2.8%	5.0%	4.9%	7.7%
2006	2.5%	4.5%	4.4%	6.9%
2007	2.6%	4.5%	4.4%	7.1%
2008	3.0%	5.4%	5.3%	8.2%

Note: Table 9.10 summarizes the annual unemployment rate in the US for years 1980-2008. The mean reflects the unweighted state-level average. Source: Authors' rendering of BLS data (2026).

Table 9.11: Summary statistics for female labor force participation in years 1980, 1990 and 2000-2008 in the US.

Year	Min	Median	Mean	Max
1980	36%	51%	50%	60%
1990	42%	58%	58%	66%
2000	49%	60%	60%	70%
2001	49%	60%	60%	68%
2002	48%	60%	60%	68%
2003	49%	61%	60%	68%
2004	49%	60%	60%	67%
2005	49%	60%	61%	67%
2006	50%	60%	60%	67%
2007	49%	60%	60%	68%
2008	51%	61%	61%	68%

Note: The unweighted state-level mean female labor force participation rate has increased from around 50% (1980) to 61% (2008). Source: Authors' rendering of IPUMS USA data (2025).

Table 9.12: Summary statistics for female college attendance rate in years 1980, 1990 and 2000-2008 in the US.

Year	Min	Median	Mean	Max
1980	23%	30%	31%	42%
1990	35%	47%	46%	57%
2000	29%	40%	41%	60%
2001	31%	41%	41%	57%
2002	29%	41%	41%	53%
2003	32%	43%	42%	53%
2004	34%	42%	43%	63%
2005	34%	42%	43%	60%
2006	33%	43%	44%	59%
2007	33%	44%	44%	60%
2008	38%	45%	46%	58%

Note: The unweighted state-level mean female college attendance rate has increased from around 31% (1980) to 46% (2008). Source: Authors' rendering of IPUMS USA data (2025).

Tables 9.13-9.15: The share values for the heat maps

Share of female inventors	
State	1980-2008
AK	4.88%
AL	5.86%
AR	4.86%
AZ	4.93%
CA	6.86%
CO	5.86%
CT	7.07%
DC	7.93%
DE	7.00%
FL	5.21%
GA	5.69%
HI	6.03%
IA	5.41%
ID	4.10%
IL	6.07%
IN	6.62%
KS	5.76%
KY	4.76%
LA	5.03%
MA	7.07%
MD	7.24%
ME	6.48%
MI	5.52%
MN	6.62%
MO	6.41%
MS	5.62%
MT	5.45%
NC	7.66%
ND	6.31%
NE	4.45%
NH	3.41%
NJ	8.52%
NM	6.83%
NV	5.93%
NY	7.41%
OH	6.24%
OK	5.24%
OR	5.41%
PA	6.55%
RI	5.90%
SC	5.10%
SD	6.03%
TN	6.24%
TX	5.55%
UT	6.00%
VA	6.48%
VT	4.41%
WA	6.28%
WI	7.66%
WV	4.10%
WY	4.24%

Share of females who have studied STEM	
State	1980-2008
AK	44.14%
AL	49.52%
AR	50.97%
AZ	44.10%
CA	43.41%
CO	43.59%
CT	46.48%
DC	46.00%
DE	47.10%
FL	47.86%
GA	49.48%
HI	46.59%
IA	46.62%
ID	42.14%
IL	46.17%
IN	46.76%
KS	46.69%
KY	50.55%
LA	50.38%
MA	47.48%
MD	47.97%
ME	48.24%
MI	45.72%
MN	46.45%
MO	47.38%
MS	53.48%
MT	43.48%
NC	50.14%
ND	48.93%
NE	48.31%
NH	45.69%
NJ	45.00%
NM	45.52%
NV	44.55%
NY	45.86%
OH	47.41%
OK	46.55%
OR	43.00%
PA	46.76%
RI	47.03%
SC	49.93%
SD	47.97%
TN	49.90%
TX	44.97%
UT	36.72%
VA	47.14%
VT	45.86%
WA	43.38%
WI	47.03%
WV	48.83%
WY	42.69%

Share of females who have studied math-intensive STEM	
State	1980-2008
AK	24.76%
AL	28.55%
AR	26.97%
AZ	23.41%
CA	23.86%
CO	25.00%
CT	25.28%
DC	29.62%
DE	26.00%
FL	25.90%
GA	28.38%
HI	26.24%
IA	21.52%
ID	20.97%
IL	24.76%
IN	23.00%
KS	22.38%
KY	25.24%
LA	28.17%
MA	25.55%
MD	28.34%
ME	21.03%
MI	25.69%
MN	23.10%
MO	24.52%
MS	29.66%
MT	22.41%
NC	27.72%
ND	21.79%
NE	22.59%
NH	23.62%
NJ	26.17%
NM	26.41%
NV	24.00%
NY	26.34%
OH	24.28%
OK	25.17%
OR	21.76%
PA	25.03%
RI	26.21%
SC	28.62%
SD	23.17%
TN	26.03%
TX	25.93%
UT	17.07%
VA	26.59%
VT	23.66%
WA	23.72%
WI	22.83%
WV	23.03%
WY	20.66%

Note: Tables 9.13-9.15 summarizes the female share values for the heat maps. Source: Authors' rendering of IPUMS USA data (2025) and USPTO data (2026).

A4 Cumulative Effects of Female Inventors

Table 9.16: Cumulative effects of female inventors on female bachelor's degree holders' propensity to have studied STEM.

Dependent variable: Studied STEM

	(1)	(2)	(3)	(4)	(5)
Share female inventor	-0.365***	-0.391***	-0.365***	-0.373***	-0.391***
	(0.020)	(0.044)	(0.092)	(0.078)	(0.074)
Female	-0.111***	-0.110***	-0.111***	-0.110***	-0.110***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Share female inventor × Female	0.364***	0.353***	0.364***	0.353***	0.353***
	(0.027)	(0.026)	(0.065)	(0.065)	(0.065)
Unemployment rate		0.003***			0.003***
		(0.001)			(0.001)
Female LFP rate		0.116***			0.116**
		(0.032)			(0.049)
Female college rate		-0.042***			-0.042
		(0.016)			(0.026)
Num.Obs.	1951617	1951617	1951617	1951617	1951617
R2	0.009	0.011	0.009	0.011	0.011
R2 Adj.	0.009	0.011	0.009	0.011	0.011
Clustered SE	No	No	Yes	Yes	Yes
State and Cohort FE	No	Yes	No	Yes	Yes
Controls	No	Yes	No	No	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Note: Table 9.16 summarizes the results of the cumulative effect of female bachelor's degree holders' propensity to have studied STEM.

Table 9.17: Cumulative effects of female inventors on female bachelor's degree holders' propensity to have studied math-intensive STEM.

Dependent variable: Studied Math-Intensive STEM

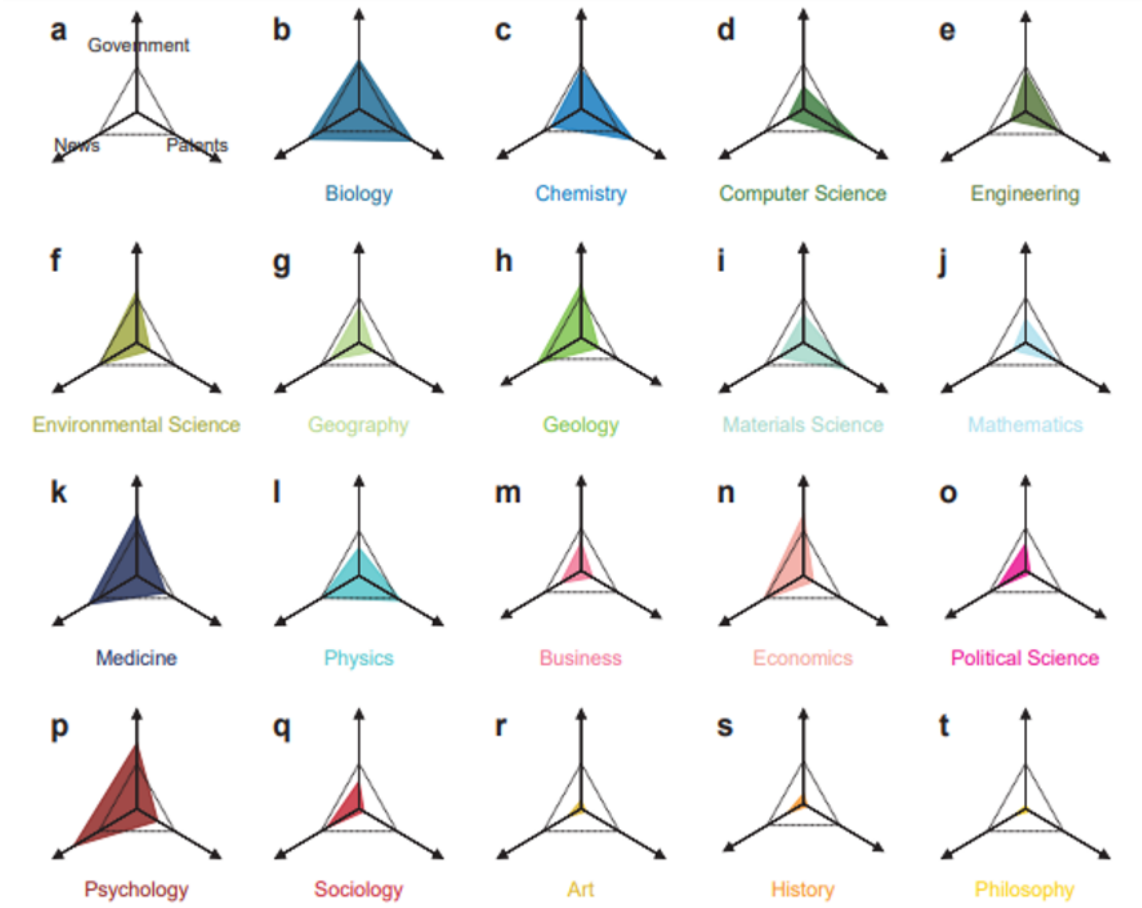
	(1)	(2)	(3)	(4)	(5)
Share female inventor	-0.499***	-0.308***	-0.499***	-0.306***	-0.308***
	(0.015)	(0.034)	(0.071)	(0.060)	(0.058)
Female	-0.193***	-0.192***	-0.193***	-0.192***	-0.192***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Share female inventor × Female	0.359***	0.345***	0.359***	0.345***	0.345***
	(0.020)	(0.020)	(0.061)	(0.062)	(0.062)
Unemployment rate		0.001**			0.001
		(0.000)			(0.001)
Female LFP rate		-0.050**			-0.050
		(0.024)			(0.036)
Female college rate		0.007			0.007
		(0.012)			(0.019)
Num.Obs.	1939389	1939389	1939389	1939389	1939389
R2	0.059	0.060	0.059	0.060	0.060
R2 Adj.	0.059	0.060	0.059	0.060	0.060
Clustered SE	No	No	Yes	Yes	Yes
State and Cohort FE	No	Yes	No	Yes	Yes
Controls	No	Yes	No	No	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Note: Table 9.17 summarizes the cumulative effects of female bachelor's degree holders' propensity to have studied math-intensive STEM.

A5 Patenting Activity by Sector

Figure 9.1: Patenting activity by sector.



Note: Figure 9.1 shows patenting by sector. The sectors that are more active in patenting include the STEM fields such as Mathematics, Physics, Chemistry, Medicine, Computer Science and Biology while the fields with patents with less extensive patenting activity include Psychology, Business, Economics, History and Philosophy (Yin et al., 2021).

A6 Declaration of AI

In this thesis, the AI tools Claude Opus 4.6 and ChatGPT Education have been used to assist the authors in the coding process and the repetitive tasks in the data analysis part, finding specific datasets and articles and formatting. Regarding the limitations of AI, the authors are aware that AI might provide inaccurate information and therefore the authors have checked that the outputs from the AI tools are true and relevant. While these tools have been used to assist the authors occasionally, the reading of the literature and the analysis in this thesis are the authors' own work, and the independent analytical and critical thinking in the writing process have been the authors' own effort.