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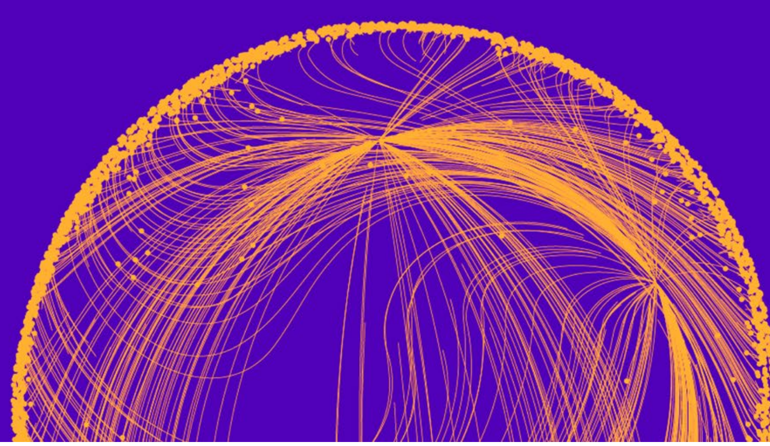

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Why Are There So Few Female Inventors?*

Atte Pudas†

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Abstract

Only a small fraction of inventors are women. Using Finnish administrative data linked to patent records, I show that educational and occupational sorting explain roughly 54% of the gender gap in patenting rates. The remaining 46% arises because women patent less than men within nearly all occupations, even after controlling for education, high school grades, and employer firm, revealing the pervasiveness of the gender differences in innovation. The career impacts of parenthood are a key mechanism: following their first childbirth, mothers' annual patenting rates decline by roughly 65%, with signs of long-term recovery, whereas fathers' patenting rates rise permanently by about 13%.

Keywords: children, gender, innovation, inventors, occupations, parenthood, patenting
JEL Codes: O31, J16, J13, J24

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1 Introduction

Over recent decades, gender gaps have narrowed in several aspects, such as employment, hours worked, and earnings (Goldin, 2006; Olivetti and Petrongolo, 2016). Women's representation in STEM (science, technology, engineering, and mathematics) has also increased gradually. Nonetheless, sizable gaps remain. In 2017, women accounted for 34% of tertiary graduates in STEM fields globally (Schmuck, 2017), and by 2024, the share of women in STEM occupations stood at only 28% (Kali Pal et al., 2024). In innovation, the gender divide is even more pronounced: the share of female patent inventors rose from less than 5% in 1980 to only 13% in Europe and the U.S. by 2019 (Toole et al., 2020; EPO, 2022).

This paper examines the factors perpetuating the gender gap in patenting. The statistics above indicate a large disparity between the share of women with competencies to innovate and women's representation among inventors, suggesting crucial differences between the careers of potential male and female inventors. I make two key contributions to understanding these differences. First, I quantify how much of the gender gap in patenting is explained by differences in educational and occupational sorting versus disparities that persist within occupations between equally qualified women and men. While the sorting channel has been extensively studied, the within-occupation differences remain less understood. I address this gap by presenting the first comprehensive analysis of within-occupation disparities in patenting across the complete set of finely specified occupations. Second, I address another gap in the literature by presenting novel evidence on the differential impacts of parenthood on women's and men's patenting activity, using a matched dynamic difference-in-differences (DID) design. As data, I use a detailed administrative panel on the Finnish population, combined with European Patent Office application records.

The following observations further motivate my analysis. Innovations, generated by inventors, drive the long-term economic growth (e.g., Romer, 1990; Aghion and Howitt, 1992). The underrepresentation of women in patenting is particularly concerning for two main reasons. First, some women with high inventive potential never become inventors, resulting in the so-called "lost Marie Curies" (Bell et al., 2019; Hoisl et al., 2022). A higher number of female inventors could, therefore, increase not only the quantity but also the quality of inventions, spurring growth through an improved allocation of talent (Hsieh et al., 2019). Second, the gender imbalance in patenting shapes what is invented and who benefits from it, as female innovators are more likely to address needs specific to women (Koning et al., 2021; Einiö et al., 2023).

The lack of women in patenting is also closely tied to broader gender differences in the labor market, such as gender segregation in education and occupations, particularly in STEM fields (e.g., Kahn and Ginther, 2017; Speer, 2023). Moreover, inventors earn substantial returns from patenting (Toivanen and Väänänen, 2012; Aghion et al., 2018; Kline et al., 2019), linking women's underrepresentation in patenting to gender pay gaps prevailing even within occupations (e.g., Goldin, 2014; Blau and Kahn, 2017). Women's lower patenting rates also align with their higher exit rates from science and engineering jobs (Preston, 1994; Hunt, 2016) and slower earnings growth relative to men (e.g., Bertrand et al., 2010; Goldin et al., 2017; Hospido et al., 2022). In addition, patents serve as a tangible measure of individuals' inventive productivity, making them a valuable lens for examining differences in productivity and value creation. A sparse literature has estimated gender differences in productivity in varying contexts and examined how they contribute to the gender pay gap (Azmat and Ferrer, 2017; Cook et al., 2020; Sin et al., 2022; Gallen, 2024).

My findings are the following. Overall, women's annual patenting rates are 88% lower than men's. Education and occupation fixed effects account for 54% of this gap, highlighting the role of differential sorting of women and men into education and occupations, consistent with previous studies linking STEM participation to inventive activity (e.g., Hunt et al., 2013; Toivanen and Väänänen, 2016; Hoisl et al., 2022).[1] The underexplored part of the patenting gap — the remaining 46% — stems from women patenting less than men within the

[1] I distinguish track-specific education and occupations at a granular level, classifying fields of study at the three-digit ISCED-2011 level and educational levels at the two-digit level (e.g., separating academic from vocational secondary education). Occupations are coded at the most detailed four- or five-digit level.

occupation-education cells. These findings carry an important policy implication: although encouraging female participation in STEM is essential for expanding the pool of potential inventors and fostering innovation, such policies alone are insufficient, as substantial gender disparities in patenting persist even within education-occupation groups.

To illustrate the pervasiveness of these disparities, I estimate the gender patenting gaps separately for each occupation. I find that women are less likely to patent than men in nearly all occupations. Moreover, as men's patenting rates rise across occupations, the absolute gender gaps widen while the relative differences remain relatively stable, with women's rates averaging roughly 50% lower than men's. These gaps persist even after controlling for age, education level, field of study, and high school grades, suggesting that differences in potential experience, competencies, and general ability cannot fully explain them. Among the 200 occupations with patenting by both women and men, 173 (86.5%) exhibit a negative gender gap estimate after accounting for the controls above, 91 of which are statistically significant at the 5% level. The remaining 27 show small, insignificant positive gaps. To exemplify, among research and development managers — the most inventor-intensive occupation — women are 2.6 percentage points (72%) less likely to patent than men, whose annual patenting rate is 3.6%. After accounting for the controls, 1.6 percentage points (or 62%) of this gap remain unexplained. These results are also robust to the inclusion of firm fixed effects, indicating that the within-occupation gender differences in patenting are not explained by women disproportionately sorting into less innovative firms.

Several mechanisms may underlie these findings. I address a gap in the literature by analyzing the relationship between parenthood and patenting activity using a matched dynamic DID design that compares within-individual trends in patenting rates between parents and comparable childless individuals. I find that women's annual patenting rates decline by roughly 65% after their first childbirth, with signs of partial recovery in the long term. Cumulatively, over the 15 years following the first childbirth, mothers lose roughly 6 years' worth of patenting relative to their pre-childbirth annual patenting rate. By contrast, men's annual patenting rates rise persistently by 13% on average during the same period, adding up to a cumulative increase of roughly twice their pre-parenthood yearly rate. However, substantial patenting gaps exist between future parents already before they have children, as well as between childless women and men. Even after controlling for age, education, and occupation, the gender patenting gap among individuals without children still amounts to roughly 39% of the gap between mothers and fathers. Taken together, my results indicate that the unequal career consequences of parenthood are a key driver of the gender gap in patenting, but cannot fully account for it.

The main contributions of this paper are the following. First, I contribute to the literature on the gender gap in innovation, which has primarily focused on how parental influence, early-life environment, exposure to innovation, and educational choices shape who becomes an inventor. The underrepresentation of women in STEM education is a key contributor to the gender gap in inventing (e.g., Jung and Ejermo, 2014; Bianchi and Giorcelli, 2020; Toivanen and Väänänen, 2016). Moreover, early exposure to STEM and innovation, especially within the family, increases a child's likelihood of becoming an inventor (Bell et al., 2019; Hoisl et al., 2022), with the child's own STEM education serving as a key mediating factor (Aghion et al., 2017). However, the role model effects are gendered, favoring boys over girls (Bell et al., 2019; Hoisl et al., 2022; Aghion et al., 2023; Breda et al., 2023).

The later stages of potential inventors' careers, beyond their education, have received less attention. A notable exception is Hunt et al. (2013), who document a strong link between the gender patenting gap and the underrepresentation of STEM-educated women in patent-intensive job tasks, such as R&D. In addition, a handful of papers have documented gender disparities in patenting within a single, specific occupational group: academic scientists (Thursby and Thursby, 2005; Whittington and Smith-Doerr, 2005; Ding et al., 2006; Whittington and Smith-Doerr, 2008; Whittington, 2011; Ceci et al., 2014). My main contribution lies in presenting the first comprehensive analysis of the pervasive within-occupation patenting gaps and in shedding light on their central role in perpetuating the gender divide in innovation.

Equally importantly, this paper advances understanding of the underlying mechanisms by providing new population-level evidence on how parenthood shapes the innovation activity of women and men. My results also indicate the presence of other relevant mechanisms within occupations and firms. These may include, at least, gender differences in monetary incentives (Toivanen and Väänänen, 2012; Hoisl and Mariani, 2017), task allocation (e.g., Hunt et al., 2013; Pető and Reizer, 2021), within-firm frictions and barriers in the innovation process (Chien and Grennan, 2024), risk and competition aversion (e.g., Gneezy et al., 2003; Niederle and Vesterlund, 2007; Booth and Nolen, 2012), and gender biases and discrimination (Ross et al., 2022).

My findings on parenthood also contribute to the extensive literature on the career effects of having children, which generally finds that women disproportionately bear the career costs (e.g., Angelov et al., 2016; Lundborg et al., 2017; Kleven et al., 2019a,b), whereas men may even experience a "fatherhood premium" in career outcomes (e.g., Korenman and Neumark, 1991; Lundberg and Rose, 2000; Correll et al., 2007; Killewald, 2013; Goldin et al., 2024).[2] Empirical evidence on the relationship between parenthood and the gender gap in patenting is scarce, with notable exceptions including Whittington (2011) and Kim and Moser (2021). In particular, the latter finds that the patenting activity of mid-twentieth-century U.S. scientist mothers stagnated or even declined after marriage during their prime childbearing years, before rebounding at older ages, whereas fathers' patenting rates remained virtually unaffected. Relatedly, Kim and Moser (2025) find that these mothers also experienced a lasting decline in publication productivity, while fathers' output did not react or even modestly increased after the assumed arrival of children.

The remainder of this paper is organized as follows. Section 2 presents the data and institutional context; Section 3 defines occupational inventiveness; Section 4 illustrates the gender inventor gap and supply of potential inventors; Section 5 examines the between- and

[2]See also Olivetti et al. (2024) for a recent review.

within-occupation differences driving the gender gap in patenting; Section 6 investigates the impacts of parenthood; Section 7 discusses other potential mechanisms; Section 8 concludes.

2 Data and Institutional Context

I use individual-year level administrative data on Finland's permanent resident population, specifically the FOLK modules, covering the period 1995–2018. The data, provided by Statistics Finland, include detailed information on variables such as education level and field, occupation, and employer firm. Occupation data are available for the years 1995, 2000, and 2004–2018, while other relevant variables are available for the entire period. The variables are measured at the end of each year. I also use data that link children born in 1970 or later to their parents, allowing me to track individuals' parental status and the timing of their children's births. In addition, I use data on high school matriculation examination results for the years 1967–2017, allowing me to observe which final exams (e.g., advanced mathematics) individuals took in high school and the grades they received.[3]

Throughout this paper, I categorize occupations at the most detailed four-digit or five-digit level. In addition, I distinguish fields of study at the three-digit level (ISCED-2011 compatible) and educational levels at the two-digit level (e.g., differentiating between high school and vocational secondary education). When I use the term 'college', I refer to all tertiary-level degrees, including doctoral degrees. In this paper, STEM refers to the following broad fields of study: (i) natural sciences, mathematics, and statistics; (ii) information and communication technologies; (iii) engineering, manufacturing, and construction; and (iv) three subfields of health: medicine, pharmacy, medical diagnostics, and treatment technology.

Furthermore, I use patent application data from the European Patent Office (EPO) to identify Finnish patent inventors and track their patenting activity. The data include all EPO patent applications (granted and rejected) filed between 1978–2019 with at least one

[3] See Supplemental Appendix A.1 for details of the school system in Finland.

Finnish inventor. The inventors are linked to the register data (see Supplemental Appendix A.2 for details), and all datasets can be merged using encrypted individual identifiers. I define inventors as individuals who are acknowledged as inventors on at least one patent application, regardless of whether it was eventually granted or rejected.[4]

The decision to use Finnish data stems from Finland being one of the few countries where patent data can be linked to individual-level register data. However, Finland also provides an intriguing context for studying gender differences in patenting, as the institutional environment itself does not inherently support such disparities. As a Nordic welfare state with globally high levels of gender equality (E.g., Hausmann et al., 2009) and an education system that is fundamentally free of charge up to and including the doctoral level, the barriers to education and career opportunities are low. In addition, discrimination based on gender is prohibited by law. However, notable gender disparities still persist, including strong segregation in both educational fields and occupations, as well as a clear gender pay gap (Statistics Finland, 2021). In addition, Finnish women's careers are disproportionately affected by parenthood compared to those of men, with long-term "child penalties" similar to those in other Nordic countries (Kleven et al., 2019a; Sieppi and Pehkonen, 2019).

3 Inventiveness of Occupations

I refer to my baseline measure of occupational inventiveness as 'inventor intensity', defined as the average annual number of patenting workers in a given occupation divided by the average total number of workers in that occupation.[5] Thus, inventor intensity captures the

[4] Aneja et al. (2024) show that majority-female inventor teams are more likely to abandon patent applications after an initial rejection, accounting for more than half of the gender gap in patents granted by the United States Patent and Trademark Office (USPTO). Since I define inventorship based on all patent applications, my results are not affected by the potentially lower persistence of female inventors in the European patent system.

[5] To my knowledge, two prior studies have attempted to define occupational inventiveness to identify firms' R&D staff. Ejermo et al. (2023) classify the most inventive occupations based on the number of inventors within three-digit occupational codes, while Kaiser et al. (2015) use first-digit "knowledge content" in the ISCO classification. I depart from these approaches by scaling inventor counts by occupation size and using the most granular occupation codes.

average annual rate at which individuals in a particular occupation are listed as inventors on patent applications. I distinguish occupations using the most specific occupation code level available.[6]

In Section 5, I analyze the gender patenting gaps across all occupations involved in patenting. Before that, it is useful to understand the characteristics of the most patenting-active occupations. Table 1 displays the occupations that fall within the top 5% of the inventor intensity distribution. These occupations are predominantly related to engineering and information technologies, as well as chemistry, pharmacy, and medicine, underscoring the strong link between STEM fields and patenting. The table displays both the overall and gender-specific inventor intensities for each occupation.[7] In addition, the two rightmost columns present the absolute and relative gender gaps in inventor intensity, showing that women are substantially less likely to patent in nearly all of the most inventor-intensive occupations. On average, for every thousand workers, there are 7.6 fewer female inventors than male inventors, which translates to women patenting 55% less frequently in these occupations. Over 80% of these occupations are male-dominated (see Supplemental Appendix Table A.2 for workforce composition), but notable exceptions exist, such as "chemists" and "pharmacologists, pathologists, and related professionals", where women make up the majority of the workforce.

Table 1 here

It is important to note that, due to the low number of female inventors, the inventor intensity of most occupations is dominated by the patenting activity of men. Women also tend to patent more in certain technology sectors, such as chemistry, compared to fields like mechanical engineering (EPO, 2022). Nevertheless, it seems that the most inventor-intensive

[6] See Supplemental Appendix A.3 for the details.

[7] To ensure completeness, I include all occupations in the analyses of this paper. Since occupations vary in size, scaling the number of inventors by occupation size is crucial for comparability. However, this approach makes the measure of inventiveness sensitive to very small occupations. As Supplemental Appendix Table A.2 shows, some occupations have a low number of inventors but are also small in size, which leads to a high inventor intensity. Therefore, the exact ranking of occupations by their inventor intensity should be regarded as an illustrative approximation.

occupations are relatively similar for women and men. Supplemental Appendix Table A.3 compares the pooled ranking of occupations by their inventor intensity and the placement of these occupations in the corresponding rankings of women and men. For instance, the twenty occupations with the highest female patenting activity all fall within the top 5% of occupations ranked by overall inventor intensity.

4 Gender Inventor Gap and Supply of Potential Inventors

To lay the foundation for the rest of the paper, I begin by illustrating the gender gap in the probability of becoming an inventor and differences in the supply of potential male and female inventors. Figure 1, Panel A shows the probability of becoming an inventor for the full birth cohorts of 1962–1982, as well as for three subpopulations of STEM college graduates: (i) all STEM graduates, (ii) those employed at least once in a top 5% inventor-intensive occupation, and (iii) those who pursued a career in these occupations for at least five consecutive years. Figure 1, Panel B displays the share of women in these samples.

Figure 1 here

Going from left to right in Figure 1 and increasing the characteristics associated with patenting, (i) the probability of becoming an inventor increases substantially for both women and men;[8] (ii) the relative increases are larger for women than for men, and the ratio of female-to-male inventing probabilities increases from 0.16 to 0.66; (iii) the absolute gender gap, however, increases from about 11 to 47 inventors per thousand individuals, and importantly; (iv) the share of women decreases from 49% to just 16%.

These findings highlight the two main factors driving the shortage of female inventors. First, the low number of women among potential inventors with a high probability of patenting, specifically, STEM-educated individuals employed in the most inventive occupations.

[8]The probabilities are low due to the rarity of inventors: in total, there are 1,575 female inventors and 10,838 male inventors in the 1962–1982 birth cohorts (see Supplemental Appendix Table A.4).

Second, even among these potential inventors, women are only about two-thirds as likely as men to become inventors. More generally, the first factor reflects gender segregation in education and occupations, while the second illustrates the patenting gap between women and men with similar education and occupations. The following section examines the contribution of these two factors to the gender gap in patenting activity.

5 Gender Differences in Patenting Activity

I use panel data covering the full population of individuals aged 18–65 in 1995, 2000, and 2004–2018 (when occupation codes are available), to estimate the following equation:

$$Patent_{iy} = \alpha + \gamma Woman_i + \lambda_y + \mathbf{X}'_{it}\beta + \varepsilon_{iy}, \tag{1}$$

where for individual i in calendar year y, the outcome variable is an indicator that equals one if the individual is listed as an inventor in a patent application filed that year, and zero otherwise; λ_t are year fixed effects; $\mathbf{X}'_{it}$ includes indicator variables for age, native language, and employment; α is a constant; ε_{iy} is the error term. In the following analysis, I progressively add indicator variables to $\mathbf{X}'_{it}$ for the full set of interactions between education level and field of study, as well as for occupation, employer firm, and high school matriculation exam grades in mathematics and the mother tongue, which serve as proxies for individual ability.[9] The coefficient of interest is γ, capturing the difference in the annual probability of patenting between women and men, net of controls. I estimate the model with ordinary least squares (OLS) and cluster the standard errors at the individual level.

Table 2 presents estimated gender gap coefficients from five specifications of equation (1), scaled by 100 for readability and interpreted as percentage point differences. The baseline

[9] I control for indicator variables capturing high school exam grades in mathematics (basic and advanced levels separately) and in mother tongue (a compulsory exam for all high school students). I include categories for individuals who did not take the math exam or did not complete high school to retain them in the sample. While high school grades are imperfect proxies of ability, achieving a high grade in advanced mathematics is positively associated with the likelihood of patenting, even after controlling for occupation and education (estimates available upon request).

estimate is statistically significant at –0.082 percentage points (col. 1). The small magnitude reflects the rarity of patenting: the average annual probability of patenting is 0.093% for men and 0.011% for women. Thus, relative to the male average, women's annual probability of patenting is roughly 88% lower.

Table 2 here

Education fixed effects absorb 42% of the baseline gender gap estimate (col. 2), and controlling for occupation fixed effects explains an additional 12% (col. 3), as the gamma coefficient declines to -0.0479 and -0.0375. Education and occupation fixed effects account for gender segregation by absorbing the portion of the gender patenting gap that arises from men being disproportionately concentrated in fields of education and occupations with higher patenting activity, such as engineering fields and professions. The remaining gender gap, therefore, reflects differences in patenting between men and women within the same education-occupation cells.[10]

Including firm fixed effects in the model does not significantly affect the gender gap coefficient once education and occupation are controlled for (col. 4).[11] Firm fixed effects account for the possibility that women and men with similar education and occupation sort into different firms with varying levels of patenting activity.[12] The fact that the residual gender gap remains virtually unchanged indicates that women with patenting-relevant education and occupations do not systematically sort into firms that, compared to those of their male

[10]I retain observations with missing occupation or firm information and assign them to corresponding "missing" categories. The information may be missing due to unemployment, full-time studying, staying home with children, retirement, or other reasons for being outside the labor force. Such observations account for 34.5% of the estimation sample. Results from a restricted sample, excluding these observations, are reported in Supplemental Appendix Table A.5. Annual patenting rates are somewhat higher in the restricted sample, 0.016% for women and 0.136% for men, reflecting the fact that patenting is rare among those not in employment. Restricting the sample does not affect the main conclusions.

[11]Throughout the observation period, at least one inventor filed a patent in a total of 3,699 firms, representing 0.49% of all observed firm IDs. On average, at least one inventor filed a patent in 443 firms per year, with a yearly range from a minimum of 208 to a maximum of 505 firms. Additionally, on average, at least two inventors patented in 174 firms annually, with a yearly range of 86 to 194 firms.

[12]A sometimes overlooked fact is that company employees produce the majority of patents: for example, between 2004 and 2018, 91% of Finnish inventors listed on EPO patent applications were company employees in the filing year, while 5% were entrepreneurs.

counterparts, have consistently weaker technological capabilities, fewer R&D resources, or otherwise place less emphasis on innovation and intellectual property creation. Rather, the within-occupation gender gap appears to be driven by gender differences arising within firms.

Finally, including indicator variables for high school grades does not significantly alter the residual gender gap once education and occupation are controlled for, although the coefficient shrinks slightly. This suggests that the gender patenting gap within education-occupation cells is not significantly explained by differences in general ability among those sorted into these groups.

In conclusion, the results suggest that gender differences in educational and occupational sorting explain approximately 54% of the gender gap in patenting activity. Thus, nearly half of the gap remains unexplained, stemming from differences within occupations between men and women with similar educational backgrounds.

To examine the pervasiveness and heterogeneity of gender gaps within occupations, I estimate the regression model described in Equation (1) separately for each occupation in which both men and women have engaged in patenting. The data include 502 occupation titles with any patenting activity: 200 have had both male and female inventors, 274 have seen patenting exclusively by men, and only 28 exclusively by women.[13] I estimate the model both without controls and including indicator variables for calendar year, age, native language, education level by field, as well as high school matriculation exam grades in mathematics and the mother tongue. The former specification captures the unconditional within-occupation gender gaps in patenting, whereas the latter estimates the 'penalties' associated with being a woman, compared to men with the same occupation, potential experience, education, and

[13] Since I observe occupations only at the end of the year, there may be some measurement error in linking occupations to patenting. Some inventors may file patents before changing occupation within the same year, leading to misassignment. Using data from the previous year would reduce this error but also introduce another issue for individuals who first switch occupations and then patent within the same year. This limitation is unlikely to affect the analysis substantially, because individuals tend to stay in the same occupation: across the 15 years from 2004 to 2018, the average inventor held 3.9 different occupation titles. Nonetheless, this measurement issue may partly explain the large number of occupations with low patenting activity, which may also reflect rare cases of individuals patenting independently while working in unrelated jobs.

ability, as proxied by high school performance.

Figure 2 displays the estimated gender gap coefficients for each occupation.[14] Figure 2, Panel A displays the estimates from the specification without controls, while Figure 2, Panel B reports the estimates from the specification including the controls listed above. The horizontal axis orders the occupations by male workers' unconditional annual probability of patenting, providing a natural benchmark for interpreting the magnitude of the estimates.[15] Occupations are categorized by their main occupational group.[16]

Figure 2 here

The estimates highlight the following novel findings. First, patenting activity is highly concentrated in a small subset of occupations, with most occupations exhibiting low rates of patenting. The majority of occupations with high patenting activity are classified as "professionals", except for the third rightmost estimate, which corresponds to R&D managers. Second, women are less likely to patent than men in a clear majority of occupations. Furthermore, comparing the estimates in Panels A and B of Figure 2 shows that, particularly at higher levels of patenting activity, the estimates remain largely statistically significant even after controlling for worker characteristics. In Panel B of Figure 2, of the 200 occupations, 173 (86.5%) have a negative gender gap coefficient (91 of which are statistically significant at the 5% level, 51 also at the 0.1% level), while the remaining 27 have a positive point estimate (none of which are statistically significant at the 5% level).

Third, comparing the estimates to men's patenting probabilities on the horizontal axis

[14] I exclude a single occupation from the figure with an average workforce size below 30, as the estimate's wide confidence intervals would reduce the readability of the figure. The excluded estimate is available upon request.

[15] Supplemental Appendix Figures A.1 and A.2 present the gender gap estimates ordered by total inventor intensity and by the share of men in each occupation, respectively. Total inventor intensity closely mirrors men's patenting probability. When ordered by the share of male workers, no clear pattern in gender patenting gaps emerges. Occupations with the largest gaps (and the highest patenting activity) tend to have a high share of male workers. However, even in patenting-active occupations dominated by women, the gender gap coefficients are systematically negative or indistinguishable from zero.

[16] The main occupational groups are based on the first digit of the occupation code. Occupations classified as "managers" or "professionals" correspond to ISCO skill level 4, while "technicians and associate professionals" fall under skill level 3. The "other" group includes occupations at skill levels 1 and 2.

shows that the gender gaps are substantial in magnitude. For example, the second rightmost coefficient in Figure 2, Panel A (-2.6 percentage points) corresponds to chemists, among whom men have an annual probability of patenting of roughly 4%. This implies that female chemists have approximately a 65% lower probability of patenting than male chemists. After controlling for individual characteristics, roughly 2.4 percentage points (92%) of this gap remain unexplained. In addition, the negative relationship between the estimated gender gaps and men's patenting probabilities is near linear, indicating that although women are also more likely to patent in occupations where men patent at higher rates, men retain a relatively stable proportional advantage. Supplemental Appendix Figure A.3 further illustrates these findings by displaying the gender gap coefficients by occupation, scaled by men's patenting probability. For example, among the most inventor-intensive 5% of occupations, the relative gender gap averages around -50%.

Finally, to account for sorting into firms, I estimate a specification that includes firm fixed effects in addition to the individual-level controls, separately for each occupation. Supplemental Appendix Figure A.4 shows that the gender gap coefficients remain either essentially unchanged or shift modestly toward zero after the inclusion of firm fixed effects. The broader pattern persists, but a larger share of estimates are insignificant: of the 200 occupations, 162 have negative point estimates (60 of which are statistically significant at the 5% level, 32 also at the 0.1% level), while the remaining 38 have positive coefficients (none of which are significant at the 5% level).

6 Parenthood and the Gender Gap in Patenting

In general, parenthood has a large and persistent negative impact on women's labor market outcomes, such as earnings, hours worked, labor force participation, and wage rates (e.g., Angelov et al., 2016; Lundborg et al., 2017; Kleven et al., 2019a,b). In contrast, men are generally either virtually unaffected or experience what is often referred to as a "fatherhood premium." Multiple papers have documented this fatherhood advantage in career outcomes, such as earnings, arguing that it may arise from employers' favorable assessments of fathers as workers, as well as from men's heightened motivation and social pressure to work harder to 'provide for the family' (e.g., Korenman and Neumark, 1991; Lundberg and Rose, 2000; Correll et al., 2007; Killewald, 2013; Goldin et al., 2024).

Direct evidence on how innovation activity is affected by parenthood is scarce. Patenting rates among scientist mothers in mid-twentieth-century U.S. stagnated or even declined during their prime childbearing years before rebounding later in life (Kim and Moser, 2021). In contrast, scientists fathers' patenting rates rose steadily through these years until declining at older ages. After first childbirth (proxied by marriage), these scientist mothers' publication rates declined and never fully recovered relative to childless scientist women, while fathers' productivity was unaffected or even increased slightly (Kim and Moser, 2025). Consistently, Whittington (2011) finds that academic mothers patent less than their childless peers. In addition, these studies show that fathers outperform childless men and all women in patenting and publication productivity.

Career interruptions due to child-rearing may have particularly negative consequences for innovation activity, given its reliance on up-to-date expertise and team-based collaboration. Career breaks may weaken professional networks and diminish individuals' engagement with the latest developments in their field. In addition, (future) mothers may seek tasks that offer predictable hours and flexible arrangements, such as part-time or remote work, which are easier to manage alongside parental responsibilities (e.g., Goldin, 2014; Goldin and Katz, 2016; Wiswall and Zafar, 2018; Kleven et al., 2019b).[17] Innovative roles may not accommodate such arrangements, as they may require extended and unpredictable hours — for example, during time-sensitive experiments in a wet lab.

I estimate matched dynamic DID regressions separately for women and men (in the spirit of e.g., Kleven et al., 2019b; Kim and Moser, 2025), in which I compare the average within-

[17] Time-use surveys conducted in Finland (e.g., Statistics Finland, 2009) and across various European countries (Craig and Mullan, 2011; García-Mainar et al., 2011) indicate that mothers devote substantially more time than fathers to childcare and related housework, such as cleaning.

individual trends in patenting activity between parents and comparable childless individuals. Although the decision to have children is endogenous, a child's arrival generates changes in parents' patenting activity that are arguably orthogonal to unobserved determinants that affect patenting more smoothly over time. For instance, women who choose to have children may differ in their inherent preferences for pursuing demanding jobs in innovation relative to women who choose to remain childless; however, such differences would be expected to shape patenting activity smoothly over time rather than producing sudden shifts, as with the birth of a child. Nonetheless, as the timing of the first childbirth is not random, the results should be interpreted with caution. Even so, they provide novel evidence on how individuals' patenting activity changes around the birth of their first child, relative to observably comparable childless individuals.

For the DID analysis, I utilize panel data covering years 1987–2019 on individuals born in 1950 or later, observed at ages 18 to 65.[18] I use matching to construct a 'benchmark' group of childless individuals for fathers and mothers who had their first child between 1988 and 2020. For each parent, the matching procedure selects a single childless individual who resembles the parent in pre-parenthood characteristics. Given that the number of childless individuals is substantially smaller than the number of parents, I allow each childless individual to be matched with multiple parents across different event years.[19] I match the parents one year before their first child is born, year by year. The matching is exact by gender, age, education level, field of study (both level and field at the 1-digit level), mother tongue (Finnish/Swedish/other), and employment status (employed/other). All matched childless individuals are assigned an event year — the birth year of the first child of their matched parent — as a pseudo-event. This way, all individuals in the estimation sample are tied to the event time frame, and the matched pairs with different event years can be stacked. Roughly 99% of all mothers and fathers are successfully matched, corresponding to about 726,000

[18]The sample is limited to individuals born in 1950 or later because childbirth data are only available from 1970 onward, which introduces increasing measurement error in child count for earlier cohorts.

[19]Supplemental Appendix Table A.7 shows the number of duplicate benchmark individuals. The presence of duplicate individual observations is accounted for when clustering standard errors.

matched father–childless man pairs and 722,000 mother–childless woman pairs. Thus, the analysis covers essentially the entire population of parents.

For the matched and stacked sample, I estimate the following equation separately for men and women:[20]

$$Patent_{iyt} = \sum_{\substack{h \in T \\ h \neq -1}} \mathbb{1}\{t = h\} \cdot \Big(\phi_t + \delta_t Parent_i\Big) + \alpha_i + \rho_y + \omega_{a(i,y)} + \varepsilon_{iyt}, \tag{2}$$

where $Patent_{iyt}$ denotes the dummy for filing a patent application for individual i in calendar year y and event year t. $Parent_i$ is an indicator for ever having children in the data. The event time $t = 0$ indicates the birth of the first child, which is a pseudo-event for childless individuals. The specification includes individual fixed effects α_i, calendar year fixed effects ρ_y, and age fixed effects $\omega_{a(i,y)}$. The coefficients of interest, δ_t, capture the average within-individual differences in patenting activity between parents and their matched childless counterparts, relative to the baseline year ($t = -1$). The set T encompasses the event window from $t = -5$ to $t = 15$, over which I examine the dynamics, as well as binned endpoint periods for $t \leq -6$ and $t \geq 16$. I apply two-way clustering at the individual and matched-pair levels to allow for dependencies between duplicates of the same childless individual and within matched parent-childless individual pairs.

Figure 3, Panel A displays the raw annual probabilities of filing a patent application for the matched sample. Figure 3, Panel B reports the dynamic DID estimates ($\hat{\delta}_t$) for women

[20] In essence, the regression model is a stacked DID design, a commonly used approach for estimating treatment effects when adoption occurs at different times and effects may be heterogeneous across units and time periods (e.g., Guryan, 2004; Cengiz et al., 2019; Fadlon and Nielsen, 2021; Jeffers, 2024; Wing et al., 2024; Bentzen et al., 2025). The strategy compares outcome trajectories of parents in each treatment cohort only to those of matched childless individuals, thereby avoiding comparisons between earlier- and later-treated parents and the resulting complications that arise in two-way fixed effects models, as noted by De Chaisemartin and d'Haultfoeuille (2020) and Goodman-Bacon (2021). In addition, the one-to-one matching ensures a constant parent-to-childless individual ratio of one across all stacked treatment cohorts, avoiding the complications from varying treated-to-control ratios noted by Wing et al. (2024). Finally, not all treatment cohorts are observed over the full estimation window due to the limited panel length (see Supplemental Appendix Table A.6). Thus, as a robustness check, I estimate the model using only always-observed cohorts — parents having their first child between 1992 and 2004 — to eliminate the potential effects of the varying estimation sample composition across event periods. The results and main conclusions remain robust. The estimates are noisier due to the smaller sample and rarity of patenting (see Supplemental Appendix Figures A.5 and A.6).

and men.[21] The pre-trends are closely parallel between the parents and childless individuals. After the birth of their first child, mothers' patenting rates begin to decline. The decrease occurs gradually over the first two years, consistent with the fact that some patent applications filed during this period may actually stem from innovation efforts undertaken before parenthood. The decline in patenting activity is considerable: the average decrease from childbirth to 15 years afterward is 0.007 percentage points, with the largest drop of roughly 0.013 percentage points occurring between 2 and 6 years after the first childbirth. Relative to the reference-year ($t = -1$) average patenting rate for mothers, these correspond to roughly 36% and 65% decreases, respectively (See Supplemental Appendix Figure A.7 for the scaled estimates). However, the upward trend in the post-period estimates beginning roughly seven years after childbirth, together with the near-zero long-term estimates, suggests that mothers' patenting rates recover over the longer term, at least partially. Nonetheless, the persistence of the reduction in the annual rates implicates a substantial cumulative impact on mothers' patenting output.

Figure 3 here

In contrast, estimates for fathers show an initial dip in patenting activity in the year of the first childbirth, followed by an increase in patenting rates beginning approximately three years afterward.[22] Given the potentially multi-year gap between the start of an innovation project and the patenting phase, the estimates are consistent with fathers experiencing a fatherhood premium in their innovation productivity after their child's birth, reflected in a subsequent increase in patenting. As noted above, the fatherhood premium may reflect both employers' favorable perceptions of fathers as workers and men's heightened motivation and pressure to increase effort and advance in their careers after having children, potentially

[21] I scale the estimates by 100 for readability: Figure 3, Panel A displays percentages and Figure 3, Panel B percentage points changes.

[22] The initial decline in the patent filings may reflect that ongoing innovation projects are delayed or paused more often in the year the child is born, when many fathers, for example, use their parental leave. However, a shift in a single estimate may also result from statistical randomness. The raw means indicate that the negative estimate is partly driven by periodical variation among the matched childless individuals.

leading to a higher proportion of fathers in inventive positions and increased patenting. On average, fathers' annual patenting increases by 0.016 percentage points over the 15 years following childbirth, corresponding to a 13% rise relative to the reference year mean. The largest increases occur 5 to 9 years after childbirth, corresponding to a rise of around 22%. Notably, the relative increases for fathers are roughly three times smaller than the corresponding declines for mothers.

These shifts in mothers' and fathers' annual patenting probabilities accumulate over time. Setting aside estimation uncertainty for the moment, the cumulative sum of the point estimates in Figure 3, Panel B, suggests that mothers experience an overall decline in patenting of close to 0.12 percentage points during the 15 years following their first childbirth, which is nearly six times their reference-period patenting probability.[23] In other words, the 15-year cumulative loss for mothers is equivalent to roughly six years of patenting at their pre-childbirth patenting rate. By contrast, fathers exhibit a cumulative 15-year increase of about 0.25 percentage points, approximately twice their baseline patenting rate.

These findings show a clear gender divergence: mothers experience a persistent decline in patenting activity after childbirth, whereas fathers' patenting rates increase permanently. In conclusion, the asymmetric career effects of parenthood have a pivotal role in perpetuating the gender gap in patenting. However, as Figure 3, Panel A shows, women's patenting rates lag behind men's even before parenthood and among childless individuals. Moreover, an additional regression analysis in Supplemental Appendix A.4 further confirms that, even after accounting for age, education, high school grades, and occupation, the patenting gap among childless individuals amounts to roughly 39% of the gap observed between mothers and fathers. Thus, while the differential impacts of parenthood amplify the gender disparities in patenting, they cannot fully account for them, pointing to additional important mechanisms.

[23] See Supplemental Appendix Figure A.8a, which plots the cumulative sums of the point estimates in Figure 3, Panel B, and Figure A.8b, which presents these cumulative estimates scaled by mothers' and fathers' reference-period ($t = -1$) patenting rates.

7 Discussion on Other Potential Mechanisms

The results above indicate the presence of additional relevant mechanisms within occupations and firms, beyond the career impacts of children. Prior literature has identified several potential mechanisms. First, financial incentives to pursue patenting may vary between women and men. Hoisl and Mariani (2017) document a 14% earnings gap between male and female patent inventors, with more than half of the gap remaining unexplained after controlling for individual characteristics, motivation and risk attitudes, job and task characteristics, parenthood, marital status, and patent quality. Additionally, Toivanen and Väänänen (2012) mention (unreported) results suggesting that female patent inventors experience lower long-term returns to patenting compared to their male counterparts.

Second, even within the same occupation, women may perform different tasks than men (Fana et al., 2021; Pető and Reizer, 2021). Research indicates that these task differences contribute to occupational gender disparities, such as wage gaps (Stinebrickner et al., 2018; Bizopoulou, 2019). Furthermore, using survey data on job characteristics of U.S. college graduates, Hunt et al. (2013) show that the underrepresentation of STEM-educated women in patenting-related job tasks is a key driver of the gender patenting gap.[24]

Women may also encounter greater friction and barriers to patenting than men. Chien and Grennan (2024) present evidence that female engineers at high-tech firms are substantially less likely to have their early-stage inventions advanced to the patent application stage than their male counterparts. Management practices and corporate culture seem to play a crucial role in this disparity: women report receiving inadequate support from management during the inventing process, as well as a lack of collaborators and advisors to evaluate the patent-worthiness of their ideas. Relatedly, Aneja et al. (2024) find that majority-female inventor teams are more likely to abandon patent applications after an initial rejection, which the authors primarily attribute to resource constraints and institutional factors, a

[24]However, Hunt et al. (2013) do not distinguish between occupations and job tasks, and do not study the allocation of tasks within occupations.

view supported also by the findings of Pairolero et al. (2025).

There may also be behavioral explanations for the gender patenting gap, such as risk and competition aversion. Patenting and research tasks are arguably competitive and involve a significant risk of failure, and typically take place in male-dominated fields and occupations. Literature indicates that women are less willing to enter competitive environments than men (Niederle and Vesterlund, 2007; Flory et al., 2015) and may perform worse in competition (Gneezy et al., 2003; Gneezy and Rustichini, 2004), especially against men (Gneezy et al., 2003; Niederle and Vesterlund, 2011). Moreover, women may have lower preferences for risk-taking than men, especially in mixed-sex environments (Booth and Nolen, 2012).[25] While differences in risk tolerance and competitiveness likely diminish during educational and occupational sorting (e.g., Buser et al., 2014; Fouarge et al., 2014; Dillon, 2018), some gender differences may persist. These lingering differences may influence who are willing to advocate for their ideas, engage in inventive tasks that carry a risk of failure, compete for resources, or persist in the face of initial setbacks.

Women may also face gender biases, discrimination, and exclusion within inventive occupations, making it more difficult for them to access inventor roles and receive recognition for their contributions. Indeed, Ross et al. (2022) document a 58% gap between men and women in the likelihood of being named as an inventor on patents produced by their research teams, and a 13% gap in the probability of being credited as an author on academic publications, both measured after controlling for team members' job titles, tenure in the team, and team fixed effects.

8 Conclusions

Women's patenting rates are 88% lower than those of men. By combining administrative Finnish population-level data with European Patent Office application records, this paper

[25]A substantial body of literature generally concludes that women tend to be more risk-averse than men (see reviews in, e.g., Croson and Gneezy, 2009; Charness and Gneezy, 2012, and their references). However, a less unanimous interpretation of the literature has also been made (Nelson, 2015).

sheds light on the factors driving the persistent gender divide in innovation. Consistent with previous literature, I document that slightly more than half of the gender gap in patenting can be attributed to educational and occupational gender segregation. Novel to the literature, I show that the remaining half of the gap arises from differences in patenting activity between men and women with similar educational backgrounds working within the same narrowly defined occupations. Women are less likely to patent in nearly all occupations, with the largest gaps found in those with the highest levels of patenting activity. These gaps persist even after controlling for individual age, education level, field of study, high school grades, and employer firm, indicating that differences in potential experience, competencies, general ability, or sorting to firms with varying levels of innovation activity have limited explanatory power for the within-occupation disparities in patenting.

As the second main contribution, I examine the link between parenthood and gender disparities in patenting using a matched dynamic difference-in-differences framework. The analysis reveals a decline in women's patenting activity of approximately 65% following the birth of their first child, with evidence of partial recovery over the long term. Over the 15 years after the first childbirth, the cumulative loss in mothers' patenting activity is equivalent to roughly six years of patenting at their pre-parenthood rate. In contrast, men exhibit a sustained increase in patenting, with an average rise in the annual rate of roughly 13% over the 15 years after becoming fathers. However, considerable differences in patenting exist between future parents before they have children, as well as between childless women and men. Together, these findings indicate that the asymmetric career consequences of parenthood are a main driver of the gender gap in innovation, although they cannot fully explain it.

The implications of my results are double-edged. On the one hand, they highlight the importance of policies that encourage women to pursue male-dominated, patent-intensive fields, such as many STEM fields, as a means of reducing gender disparities in patenting and unlocking women's untapped inventive potential. Such policies might involve, for instance, exposing students in primary and secondary education to female role models through school visits or mentoring programs, as well as implementing initiatives that make STEM fields more inclusive and appealing to women. On the other hand, my results also indicate that these measures, while valuable, are insufficient on their own, as substantial and pervasive disparities persist within occupations and firms.

My findings also indicate that policies addressing the unequal career effects of parenthood could enhance women's inventive productivity and strengthen their representation among inventors. In addition, other mechanisms contributing to the gender disparities in patenting may include differences in monetary incentives, access to resources, frictions in the inventive process, and discrimination. In these cases, corporate policy reforms and greater support for female inventors could make a meaningful difference. At the same time, gender gaps in patenting may also stem from behavioral factors, such as differences in risk and competition preferences, making it less clear whether and how these factors should be addressed through policy measures. Nonetheless, both policymakers and firms seeking to foster innovation should examine whether aspects of working conditions, work culture, and innovation processes unintentionally reinforce gender disparities and result in inefficient use of women's innovation potential. Understanding why women continue to lag behind men in patenting, even after entering patent-active occupations and firms, presents a promising avenue for future research.

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Figures and Tables

(A) Probability of Becoming an Inventor

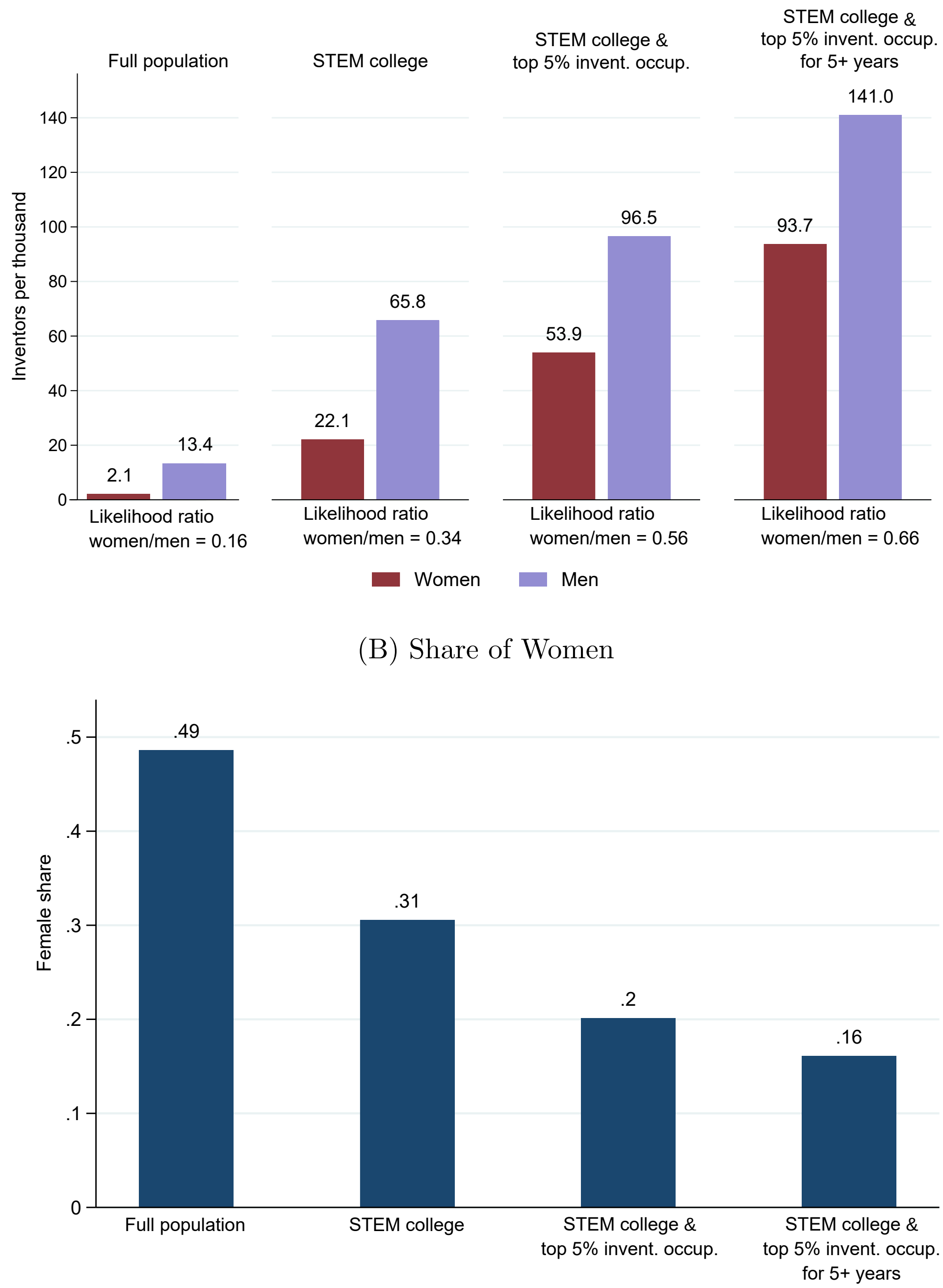

Figure 1: Gender Inventor Gap and Supply of Potential Female Inventors

Notes. Panel A displays the share of female and male inventors among all women and men, respectively, for the full population of birth cohorts from 1962 to 1982 and for the three subsamples of STEM college graduates. The likelihood ratios of female-to-male inventor probabilities are shown below the bars for each sample. Panel B displays the share of women in the samples. The sample sizes and number of inventors in the samples are presented in Supplemental Appendix Table A.4.

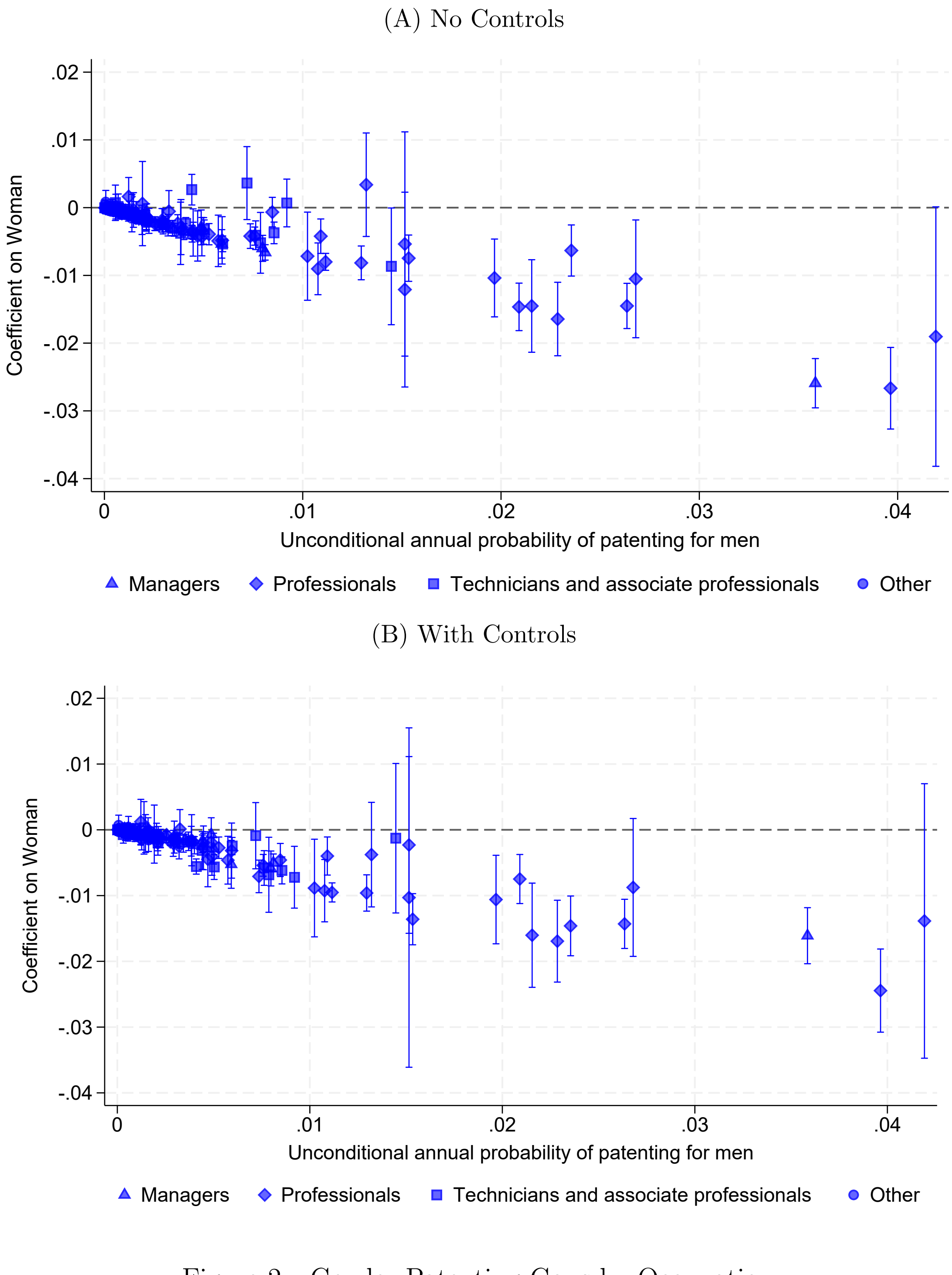

Figure 2: Gender Patenting Gaps by Occupation

Notes. This figure presents the occupation-specific gender gap coefficients, along with their 95% confidence intervals. The coefficients are estimated with the regression model in Equation (1) separately for each occupation. Panel A displays the unconditional gender gaps. Panel B displays estimates from a specification that includes fixed effects for calendar year, age, native language, high school grades, and education level by field. The horizontal axis orders occupations by the patenting probability of male workers.

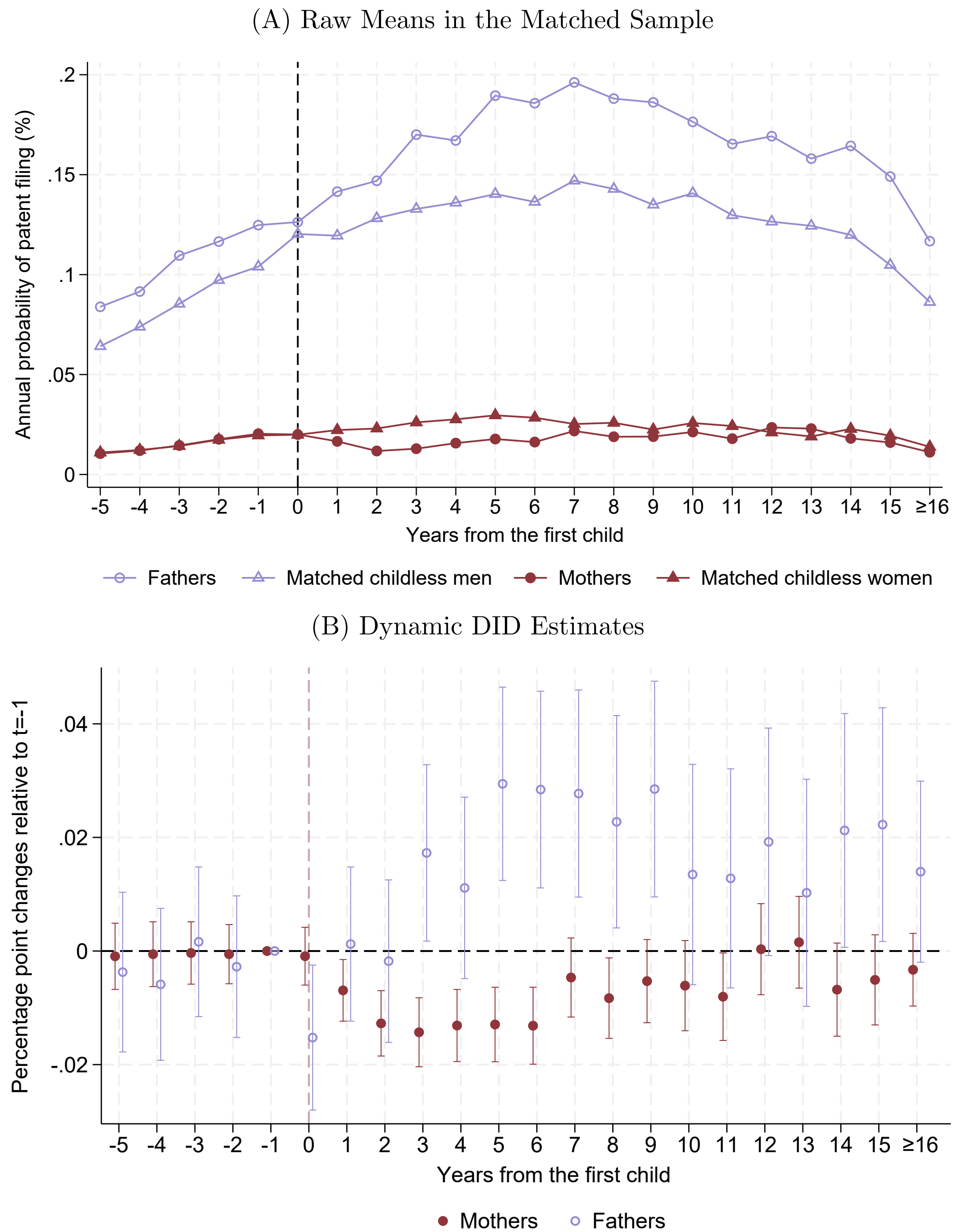

Figure 3: Changes in Annual Patenting Rates Around the First Childbirth

Notes. Panel A displays the raw probabilities of patenting for parents and matched benchmark individuals in the estimation window, expressed as percentages. Panel B plots point estimates and 95% confidence intervals, estimated separately for women and men using the dynamic DID model in Eq. (2), scaled by 100 to represent percentage point changes. The outcome variable is an indicator for filing a patent application in a given year. The model includes calendar year, age, and individual fixed effects. The sample comprises matched parent–childless pairs from cohorts born in 1950 or later, observed from 1987 to 2019. Standard errors are clustered at the individual and the matched-pair levels.

Table 1: Top 5% Inventor-Intensive Occupations

	Mean total inventors per 1,000 workers (I)	Mean female inventors per 1,000 female workers (I_w)	Mean male inventors per 1,000 male workers (I_m)	Absolute gender gap: $I_w - I_m$	Relative gender gap: $(I_w - I_m)/I_m$
1. Research and development managers	30.3	9.9	35.8	-25.9	-0.72
2. Pharmacologists, pathologists and related professionals	28.8	22.8	41.8	-19.0	-0.45
3. Telecommunications researchers	25.3	16.3	26.8	-10.5	-0.39
4. Chemists	25.1	13.0	39.5	-26.5	-0.67
5. Electronics and telecommunications engineers	24.5	11.8	26.3	-14.5	-0.55
6. Chemical engineers	21.8	17.2	23.6	-6.4	-0.27
7. Physicists and astronomers	19.1	6.4	22.7	-16.3	-0.72
8. Information technology researchers	18.9	7.0	21.5	-14.5	-0.67
9. Telecommunications engineers	18.0	9.3	19.7	-10.4	-0.53
10. Mathematicians, statisticians and related professionals	17.4	18.5	16.4	2.1	0.13
11. Professors	16.9	6.2	20.6	-14.4	-0.70
12. Social science and related professionals	15.7	0	24.2	-24.2	-1.00
13. Electrical engineers	14.7	7.9	15.3	-7.4	-0.49
14. Mining engineers, metallurgists and related professionals	13.7	16.6	13.3	3.3	0.26
15. Physical and engineering science associate professionals	12.5	5.8	14.5	-8.7	-0.60
16. Electronics engineers	12.0	4.8	12.9	-8.1	-0.63
17. Health professionals (except nursing)	11.9	9.8	15.1	-5.3	-0.35
18. Rubber- and plastic-products machine operators	10.6	0	13.2	-13.2	-1.00
19. Mechanical engineers	10.6	3.1	11.1	-8.0	-0.72
20. Chemical engineering technicians	9.4	9.9	9.2	0.7	0.08
21. Architects, engineers and related professionals not elsewhere classified	8.3	7.8	8.5	-0.7	-0.08
22. Biologists, botanists, zoologists and related professionals	8.3	6.7	10.9	-4.2	-0.39
23. Electronics and telecommunications technicians	7.9	4.8	8.6	-3.8	-0.44
24. Mining and metallurgical technicians	7.9	10.8	7.2	3.6	0.51
25. Production and operations managers in manufacturing	7.5	2.0	8.0	-6.0	-0.75
26. Manufacturing managers	7.3	1.5	8.1	-6.6	-0.82
27. Electronics engineering technicians	6.9	3.6	7.6	-4.0	-0.53
28. Engineering professionals not elsewhere classified	6.6	3.4	7.6	-4.2	-0.55
29. Industrial and production engineers	6.4	3.1	7.3	-4.2	-0.57
30. Environmental engineers	6.4	3.1	10.2	-7.1	-0.70
31. Product and garment designers	5.6	1.7	10.7	-9.0	-0.84
32. Chemical and physical science technicians	5.2	2.6	7.4	-4.8	-0.65
33. Managers of small enterprises in manufacturing	5.2	0.6	5.9	-5.3	-0.90
34. Computer network professionals	5.1	1.1	5.9	-4.8	-0.81
35. Wood processing and chemical engineering technicians	5.0	7.1	4.4	2.7	0.60
36. Health professionals (except nursing) not elsewhere classified	4.9	3.0	14.9	-11.9	-0.80
37. Electrical engineering technicians	4.8	1.8	5.1	-3.3	-0.64
38. Pet producers	4.6	0	13.0	-13.0	-1.00
39. Other specialist managers not elsewhere classified	4.3	1.6	5.1	-3.5	-0.69
40. Policy and planning managers	4.2	2.0	5.0	-3.0	-0.61
41. Prosthetist-orthotists	4.1	0	6.1	-6.1	-1.00
42. Mechanical engineering technicians	4.0	1.8	4.1	-2.3	-0.57
43. Information and communications technology service managers	3.8	0.3	4.4	-4.1	-0.93
44. Assistants and part-time lecturers (university)	3.5	1.3	5.2	-3.9	-0.74
45. Managers of small enterprises of business services enterprises	3.4	0.8	4.5	-3.7	-0.82
Column average	11.07	5.97	13.53	-7.56	-0.55

Notes. This table describes the inventor intensity of occupations that fall within the top 5% of the inventor intensity distribution. The means are calculated over the years 1995, 2000, and 2004–2018. See Supplementary Appendix A.3 for calculation details and Supplementary Appendix Table A.2 for occupation sizes and gender compositions.

Table 2: Gender Patenting Gap

	(1)	(2)	(3)	(4)	(5)
	Outcome: patent dummy				
Woman	-0.0820***	-0.0479***	-0.0375***	-0.0383***	-0.0357***
	(0.0011)	(0.0011)	(0.0011)	(0.0012)	(0.0012)
% of the baseline coefficient in column (1) absorbed		42%	54%	53%	57%
Adj. R^2	0.0007	0.0132	0.0183	0.0323	0.0184
Observations	57,153,972	57,153,972	57,153,972	57,153,972	57,153,972
Education level $\times$ field FE	-	Yes	Yes	Yes	Yes
Occupation FE	-	-	Yes	Yes	Yes
Firm FE	-	-	-	Yes	-
High school grade FE	-	-	-	-	Yes

Notes. This table provides the estimated gender gap coefficients $\hat{\gamma}$ from five different specifications of equation (1), estimated with OLS. The dependent variable in each regression is a patenting indicator, and each specification includes indicator variables for calendar year, age, native language, and employment status. Educational fields are classified at the three-digit level (ISCED-2011 compatible); educational levels are at the two-digit level (e.g., differentiating between high school and vocational secondary education). Occupations are categorized at the most detailed four-digit or five-digit level. The coefficients are multiplied by 100 for readability and therefore represent percentage point differences. The estimation sample is a panel of individuals observed during the years 1995, 2000, and 2004–2018 at ages 18–65. I retain observations with missing firm or occupation information and assign them to "missing" categories. Robust standard errors are clustered at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

ONLINE APPENDIX

Why Are There So Few Female Inventors?

Atte Pudas[†]

December 13, 2025

A Appendices

A.1 School System in Finland

Education is fundamentally free of charge in Finland. The school system starts with compulsory basic education at age 7. After nine grades, individuals can apply to high school or vocational education. High school studies culminate in the matriculation examination, which is a standardized nationwide set of separate subject-specific final exams. The final examinations are graded on a 7-point scale, with the lowest grade indicating a failing score.[1] The grades are based on students' performance relative to all other test takers nationwide (e.g., the top 5% receive the highest grade). The final exams include subjects such as mother tongue and literature, mathematics (basic or advanced level), foreign languages, humanities such as history, and natural sciences such as physics or chemistry. Only the final exam for mother tongue and literature has always been mandatory. Otherwise, the students can choose, with some restrictions, which exams to take. To be eligible for a final exam, a student must have completed all compulsory courses in the subject. Additionally, performing well on the exam usually necessitates knowledge gained from elective courses. Consequently, the final exams students choose to take are closely aligned with the courses they took, and their performance on these exams should strongly reflect their overall learning throughout high school.

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[1]The grades are (from lowest to highest) as follows: I, A, B, C, M, E, and L. Originally, the grading system included only four grades, I, A, C and L. Grades B and M were introduced in 1970, and E in 1996.

After completing secondary education, individuals can apply to universities and universities of applied sciences, which I will collectively refer to as 'college' in this paper. During the years studied in this paper, most applicants to specific degree programs were required to pass a program-specific entrance exam. Applicants were then ranked based on their performance in this exam and prior academic achievements, typically their matriculation exam grades in program-related subjects. Entry into many degree programs, including many STEM fields, is competitive. Thus, students aiming for an engineering degree, for example, benefit from excelling in subjects like advanced mathematics, physics, and chemistry in high school.

A.2 Linking of the Inventors to Register Data

I obtain data on Finnish patent inventors and applicants from the OECD REGPAT Database (Maraut et al., 2008). The database fully derives the European Patent Office's (EPO) Worldwide Statistical Patent Database (PATSTAT Global).

Inventors were linked to Finnish register data in Statistics Finland (SF) using their full names, home addresses (including postal codes, street names, and numbers), patent applicant firm names and addresses, and the year of the patent application. The primary challenges in linking inventors arise from two factors: (i) common names, which correspond to a large number of individuals in the register data, and (ii) significant variations in the format of names and addresses between patent applications and the register data. As a result, effective linking requires cleaning the name and address data and interpreting correct matches based on information about individual addresses and employers, in addition to the inventor names.

I combine the results of two matching efforts to create a dataset of Finnish inventors in EPO patent applications filed between 1978 and 2019, linked to register data. Each linked inventor is assigned a unique encrypted ID number, which connects them to all individual-level datasets of SF.

The first matching was conducted in 2013, in which inventors from patent applications filed between 1978 and 2012 were linked to the register data by a civil servant at SF. The resulting matched inventor data has been used in several published papers (Aghion et al., 2018, 2023, 2022, 2017). This process used the aforementioned patent information along with corresponding non-encrypted name and address data from SF's databases. Essentially, the civil servant cleaned the raw names and addresses in the patent data and used them to exact matching. Various combinations of matching variables were employed, with the matching year also sometimes differing from the patent application year (e.g., matching an inventor in a 2005 patent with the firm name and address data from 2004 or 2006). The list of all variable combinations and the corresponding matching rates can be provided upon request.

The second round of matching was carried out in 2024 for patent applications filed between 1978 and 2019. The matching was performed by an employee of SF using a matching algorithm developed for this purpose (Berge, 2023). Comprehensive documentation and all corresponding R-code for the algorithm are publicly available in GitHub lrberge/linking_winst. The algorithm utilizes the same information from the inventor and register data as the first matching, but uses more advanced name cleaning and Bayesian match quality assessment algorithms. The algorithm is designed to be transparents and stringent in determining which matches are considered accurate.

I combine the results from the two matching efforts for the overlapping period 1978–2012. The combined matching successfully identifies a match in the register data for 93% of the inventor-patent observations in the overlapping period. The two rounds of matching appear to be complementary. For 63% of the matched inventor-patent observations, both matching rounds identified the same individual in the register data; 21% were linked solely by the old matching and 14% exclusively by the new matching. Importantly, only 1.3% of the matches are such that the two matching rounds link different individuals in the register data to the same inventor-patent observation (in which case at least one of the matches must be a false positive). In these cases, I retain the result from the more recent matching.

Several factors likely account for the differences between the results of the first and second matching rounds. First, during the initial matching round, the civil servant developed several combinations of matching variables, some of which were less stringent than those applied by the more recent algorithm. The civil servant also utilized his knowledge of Finnish naming conventions, including the fact that many streets have both Finnish and Swedish names. Second, the thorough name data cleaning in the more recent matching algorith may have enabled the identification of matches that were previously missed. Third, the register data may have been supplemented and refined retrospectively. Given these considerations, and in the absence of evidence indicating a substantial presence of false positive matches, I combine the results from both matching rounds.

In total, for EPO patent applications filed between 1978 and 2019, the combined matching successfully identifies a person in the register data for 90% (79,446) of all inventor-patent observations, which translates to 22,557 unique matched Finnish inventors. At the patent application level, all inventors were matched in 80% of the patent applications; in 14% of the patents, some, but not all, inventors were matched; and in the remaining 7% of patent applications, no inventor matches were found.

A.3 Inventiveness of Occupations

I define the inventor intensity of occupations as follows. For each year and occupation, I first count the number of individuals listed as inventors on at least one patent application filed in the given year. So, importantly, I do not calculate the annual number of persons in a given occupation who have *ever* patented, but the number of persons who file a patent while having the given occupation. Therefore, the same inventor can be counted multiple times for multiple occupations if she patents in several years and occupations. Then, I calculate the mean annual number of these inventors for each occupation over the years 1995, 2000, and 2004–2018, the years for which the occupation and patenting data is available. To calculate the inventor intensity, I then divide the mean number of inventors by the corresponding mean number of all workers in the given occupation.

Essentially, I distinguish occupations at the finest 4-digit level (ISCO-compatible) or national 5-digit level when available. More precisely, I distinguish occupations by their name (at the finest occupation level) in the data. I use the occupation names as they are more stable in the data across years than occupation codes — the occupation classification was updated in 2010, and as a result, some occupations received new codes (while the occupation name did not necessarily change), and some occupations were combined into bigger units or divided into smaller units with new codes. However, also the occupation names of effectively same occupations may have changed. Therefore, the number of years each occupation name appears in the data varies.

If I wanted to follow individuals' occupations over time, I would have to use a crosswalk between the two occupation classifications. However, for the purposes of the analyses in this paper, it is not a threat if the effectively same occupation appears twice with two different names. Also, even with a crosswalk between the two classifications, it is not clear how to allocate workers to, for example, two occupations in the old classification that were combined in the new classification.

A.4 Parenthood and Patenting: Additional Descriptive Regression Analysis

Here, I describe the association between parenthood and patenting activity for women and men using a simple regression. For the first analysis, I use panel data on full population of individuals born in 1950 or later, observed between ages 18 and 65 in the years 1995, 2000, and 2004–2018, to estimate the following equation:[2]

$$\begin{aligned} Patent_{iy} = \alpha + \beta_0 Woman_i + \beta_1 HasChidlren_{iy} + \beta_2 HasChidlren_{iy} \times Woman_i \\ + \lambda_y + \mathbf{X}'_{iy}\delta + \varepsilon_{iy}, \end{aligned} \tag{A.1}$$

where $HasChidlren$ is a indicator variable for whether individual i in calendar year y has

[2]The sample is limited to individuals born in 1950 or later because childbirth data are only available from 1970 onward, which introduces increasing measurement error in child count for earlier cohorts. The restriction on years reflects the availability of occupation data.

any children. Otherwise, the model is similar to Equation (1). The parameters of interest are β_0, which reflects the gender gap (women − men) in the annual probability of patenting among individuals who do not have children (but may have them later); β_1, which reflects the association between having children and patenting among men (fathers − childless men); and β_2, which indicates how this association differs for women. In addition, the following sums are informative: $\beta_1+\beta_2$ captures the association between having children and patenting among women (mothers − childless women), and $\beta_0+\beta_2$ captures the gender gap in patenting among parents (mothers − fathers).

The results are presented in Table A.1. The coefficients are scaled by 100 and interpreted as percentage point differences. Column (1) reports the gender gap estimate of -0.0875 percentage points (-88% compared to men's raw mean) from the baseline specification.[3] Column (2) introduces the dummy for having children, interacted with the female dummy. Notably, the magnitude of the coefficient $\hat{\beta}_0$ decreases substantially from column (1) to column (2). However, a strong negative association remains, indicating that being a woman is negatively associated with patenting activity among individuals without children. The estimate of $\hat{\beta}_1$ indicates that having children is positively associated with men's patenting rates, while for women, the sum $\hat{\beta}_1 + \hat{\beta}_2$ indicates a negative association.

In column (3), the inclusion of fixed effects for education, occupation, and high school grades reduces the magnitude of these estimates by roughly half, but the overall patterns remain unchanged. Women without children are 0.0243 percentage points less likely to patent than childless men with the same age, education, high school grades, and occupation. Compared to women without children, mothers have an additional 'penalty' of 0.0097 percentage points. Furthermore, fathers patent at a rate 0.0288 percentage points higher than comparable childless men. Driven by the negative association for mothers and the positive association for fathers, the gender patenting gap among childless individuals amounts to roughly 39% of the gap between mothers and fathers (β_0 versus $\beta_0 + \beta_2$).

[3]The raw average annual patenting probability is 0.099% for men and 0.012% for women in the estimation sample.

Table A.1: Gender Patenting Gap and Parenthood

Variable	Coef.	(1)	(2)	(3)
		Outcome: patent dummy		
Woman	$\hat{\beta}_0$	-0.0875***	-0.0519***	-0.0243***
		(0.0013)	(0.0012)	(0.0013)
HasChildren	$\hat{\beta}_1$		0.0554***	0.0288***
			(0.0024)	(0.0023)
HasChildren × *Woman*	$\hat{\beta}_2$		-0.0771***	-0.0385***
			(0.0025)	(0.0023)
	$\hat{\beta}_1 + \hat{\beta}_2$		-0.0217***	-0.0097***
			(0.0009)	(0.0009)
	$\hat{\beta}_0 + \hat{\beta}_2$		-0.1290***	-0.0628***
			(0.0022)	(0.0022)
Adj. R^2		0.0007	0.0008	0.0191
Observations		50,219,204	50,219,204	50,219,204
Education level × field FE		-	-	Yes
Occupation FE		-	-	Yes
High school grades FE		-	-	Yes

Notes. This table provides the results from three different specifications of equation (A.1), estimated with OLS. The dependent variable in each regression is a patenting indicator. Each specification includes dummy variables for calendar year, age, native language, and employment. Educational fields are classified at the three-digit level (ISCED-2011 compatible); educational levels are at the two-digit level (e.g., differentiating between high school and vocational secondary education). Occupations are categorized at the most detailed four-digit or five-digit level. The coefficients are multiplied by 100 for readability and represent percentage point differences. The estimation sample is a panel of individuals born in 1950 or later, observed during the years 1995, 2000, and 2004–2018 at ages 18–65. I retain observations with missing occupation information and assign them to a "missing" category. Robust standard errors are clustered at the individual level. $^{***}\ p < 0.01$, $^{**}\ p < 0.05$, $^{*}\ p < 0.1$

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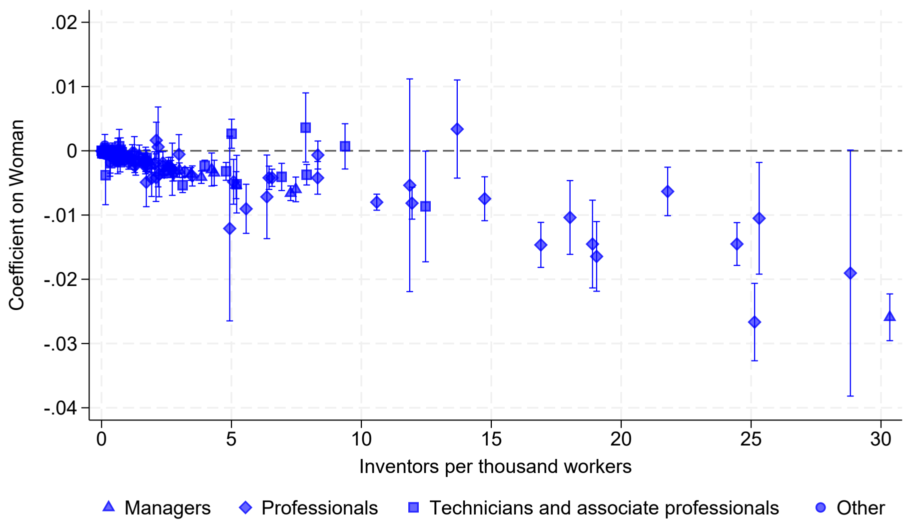
A.5 Additional Figures

(a) No Controls



(b) With Controls

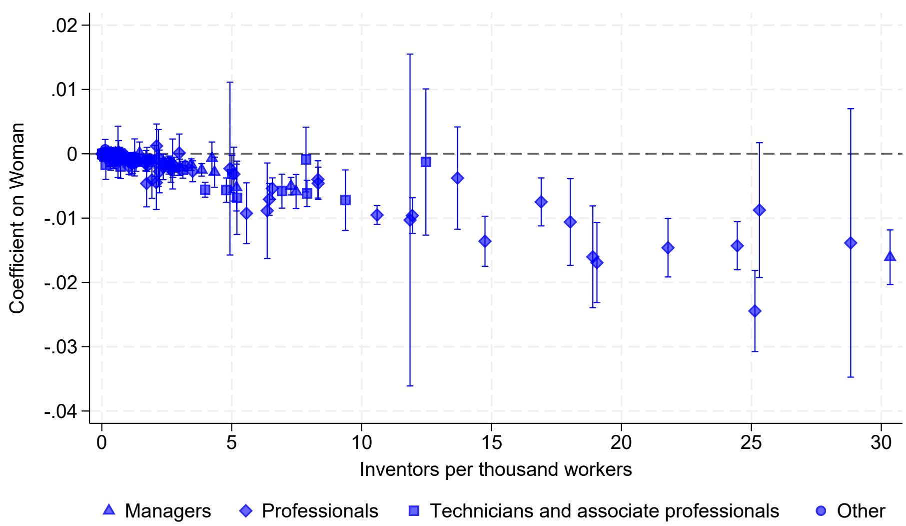
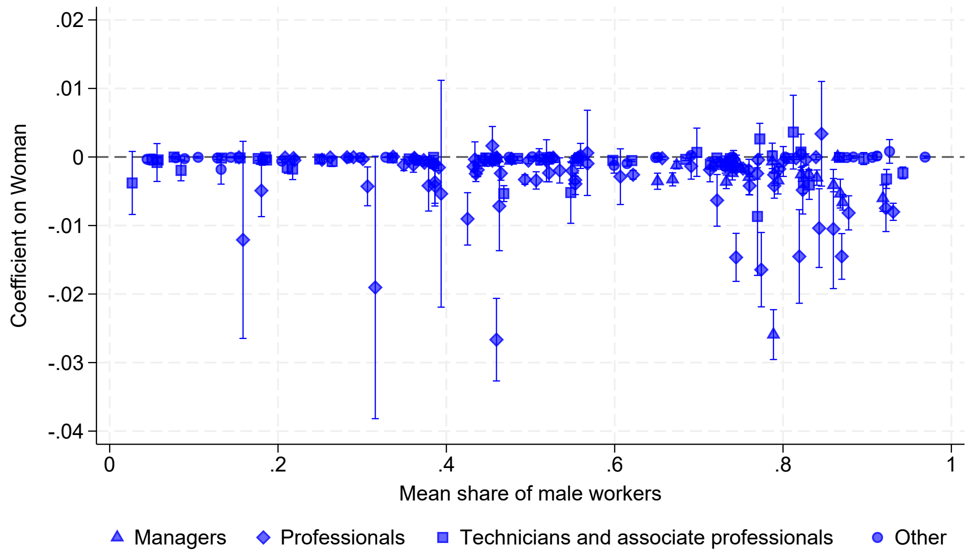


Figure A.1: Gender Patenting Gaps by Occupation, Sorted by Inventor Intensity

Notes. This figure shows the estimated gender patenting gaps and their 95% confidence intervals by occupation, ordering the occupations by the inventor intensity. The coefficients are estimated with a model described in Equation (1), separately for each occupation. Figure A.1a shows the estimates from regressions without control variables. Figure A.1b shows the estimates from regressions that control for indicator variables for year, age, native language, education level by field, and high school matriculation examination grades for mathematics and mother tongue. The estimation sample is a panel of individuals observed during the years 1995, 2000, and 2004–2018 at ages 18–65. I exclude a single occupation with an average workforce size below 30 from the figure, as the estimate's wide confidence intervals would reduce the figure's readability. Standard errors are clustered at the individual level.

(a) No Controls



(b) With Controls

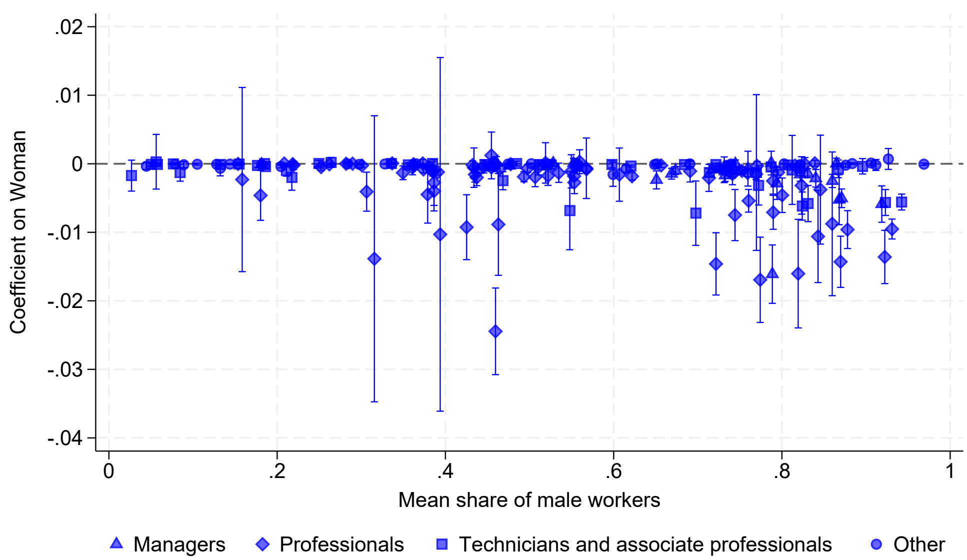
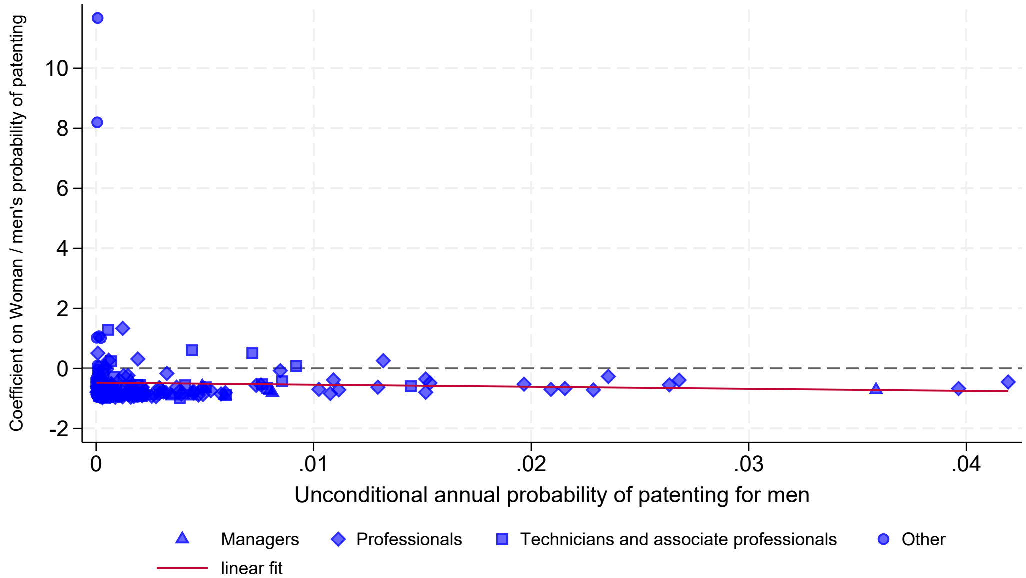


Figure A.2: Gender Patenting Gaps by Occupation, Sorted by Male Share

Notes. This figure shows the estimated gender patenting gaps and their 95% confidence intervals by occupation, ordering the occupations by the average share of male workers. The coefficients are estimated with a model described in Equation (1), separately for each occupation. Figure A.2a shows the estimates from regressions without control variables. Figure A.2b shows the estimates from regressions that control for indicator variables for year, age, native language, education level by field, and high school matriculation examination grades for mathematics and mother tongue. The estimation sample is a panel of individuals observed during the years 1995, 2000, and 2004–2018 at ages 18–65. I exclude a single occupation with an average workforce size below 30 from the figure, as the estimate's wide confidence intervals would reduce the figure's readability. Standard errors are clustered at the individual level.

(a) All Patenting-Active Occupations
No Controls



(b) Top 5% Inventor-Intensive Occupations
No Controls

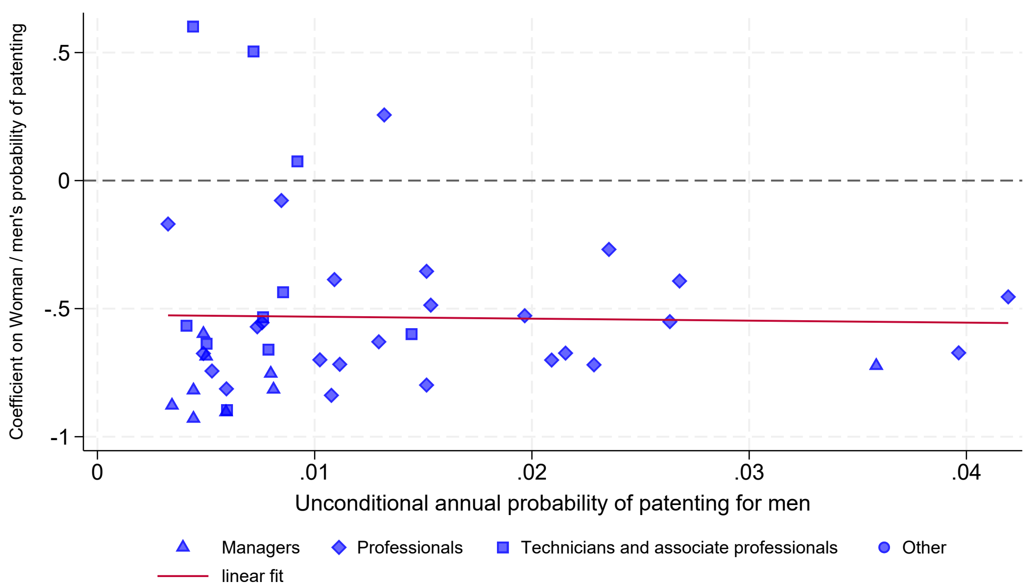


Figure A.3: Gender Patenting Gaps to Men's Patenting Probability by Occupation

Notes. This figure displays the by-occupation unconditional gender patenting gaps from Figure 2, Panel A, divided by men's probability of patenting (which is displayed on the x-axis). Figure A.3a displays the scaled estimates for all occupations with both male and female patenting activity, and Figure A.3b zooms into the top 5% most inventor-intensive occupations.

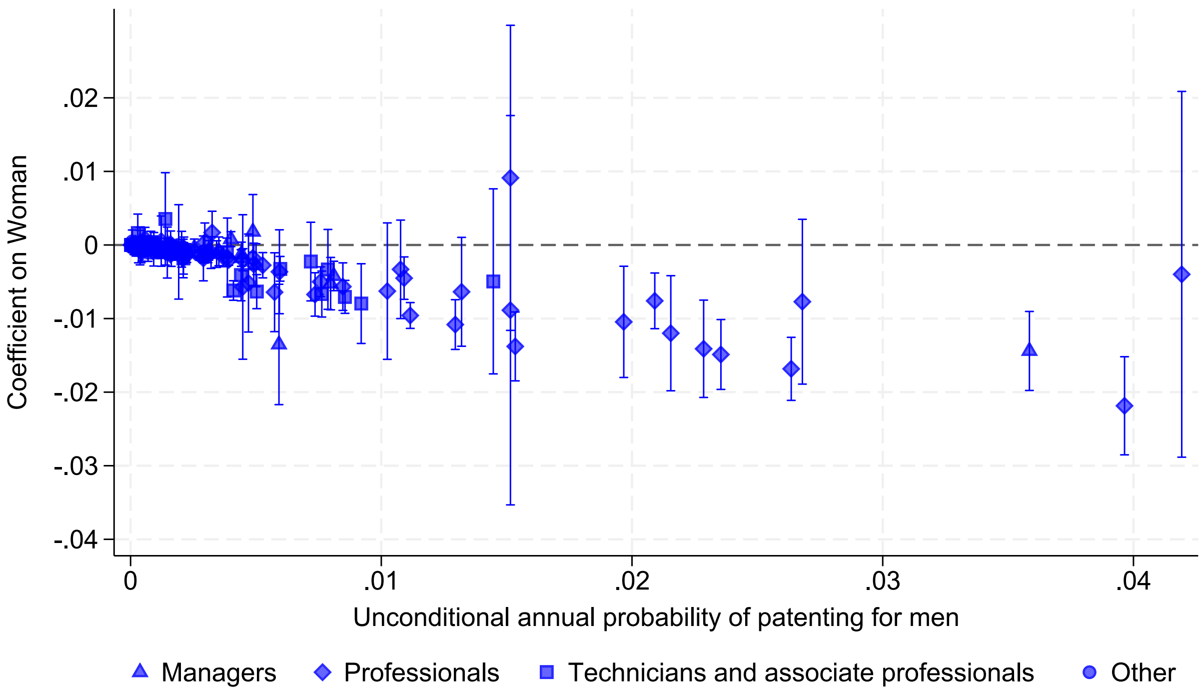
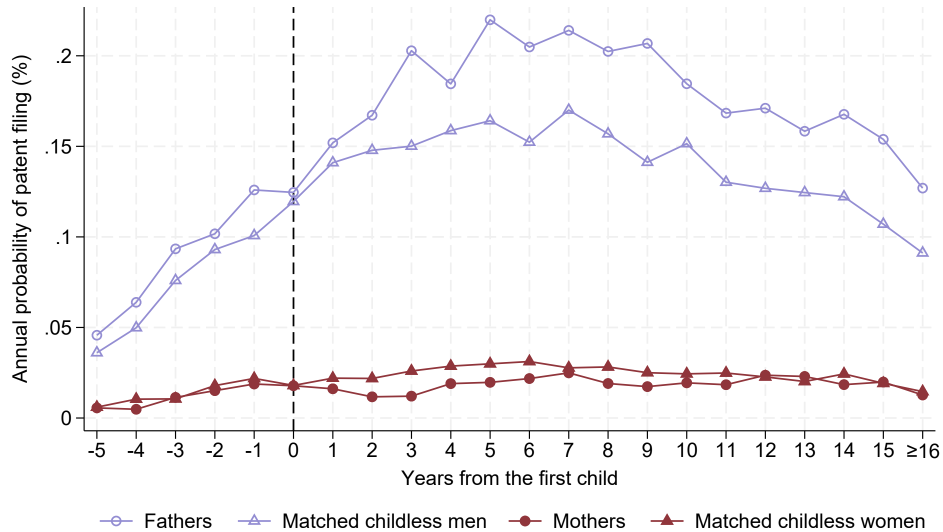


Figure A.4: Gender Patenting Gaps by Occupation, Controlling for Firm FEs

Notes. This figure shows the estimated gender patenting gaps and their 95% confidence intervals by occupation. The coefficients are estimated with a model described in Equation (1), separately for each occupation. The regression specification includes indicator variables for year, age, native language, education level by field, high school matriculation examination grades for mathematics and mother tongue, and firm. The estimation sample is a panel of individuals observed during the years 1995, 2000, and 2004–2018 at ages 18–65. I exclude a single occupation from the figure with an average workforce size below 30, as the estimate's wide confidence intervals would reduce the readability of the figure. Standard errors are clustered at the individual level.

(a) Raw Means in the Matched Sample



(b) Dynamic DID estimates

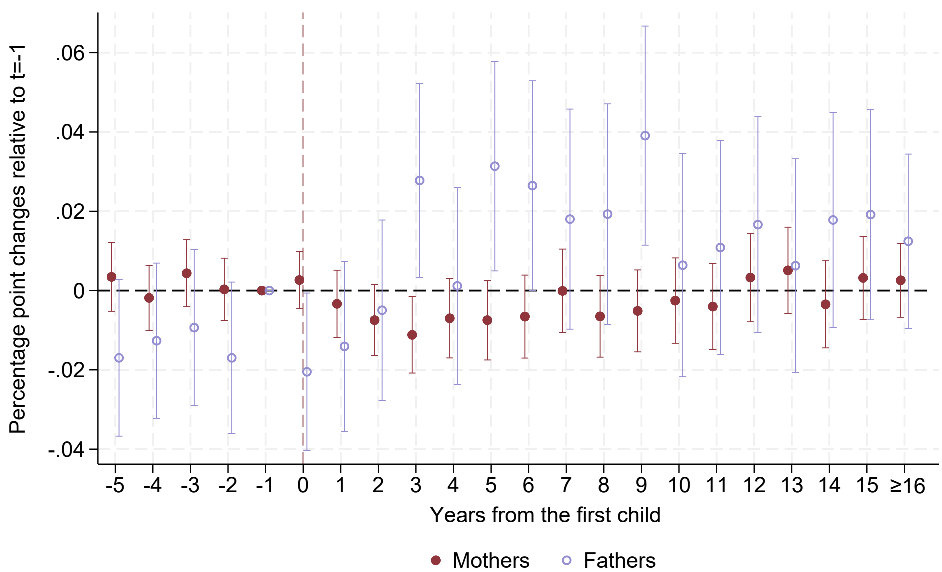


Figure A.5: Changes in Annual Patenting Rates Around the First Childbirth: Sample Trimmed to Treatment Cohorts 1992–2004

Notes. Figure A.5a displays the raw patenting rates for parents and matched benchmark individuals in the estimation window, expressed as percentages. Figure A.5b plots point estimates and 95% confidence intervals from the dynamic DID model in Eq. (2), scaled by 100 to represent percentage point changes. The outcome variable is an indicator for filing a patent application in a given year. The model includes calendar year, age, and individual fixed effects. Standard errors are clustered at the individual and the matched-pair levels. The sample comprises matched parent–childless pairs from cohorts born in 1950 or later, observed from 1987 to 2019. The sample is further restricted to parents who had their first child between 1992 and 2004, and can be observed throughout the estimation window $t \in [-5, 15]$. Parents are matched with childless individuals one year before their first child is born. The matching is exact by gender, age, mother tongue, education level and field (at the 1-digit level), and employment status.

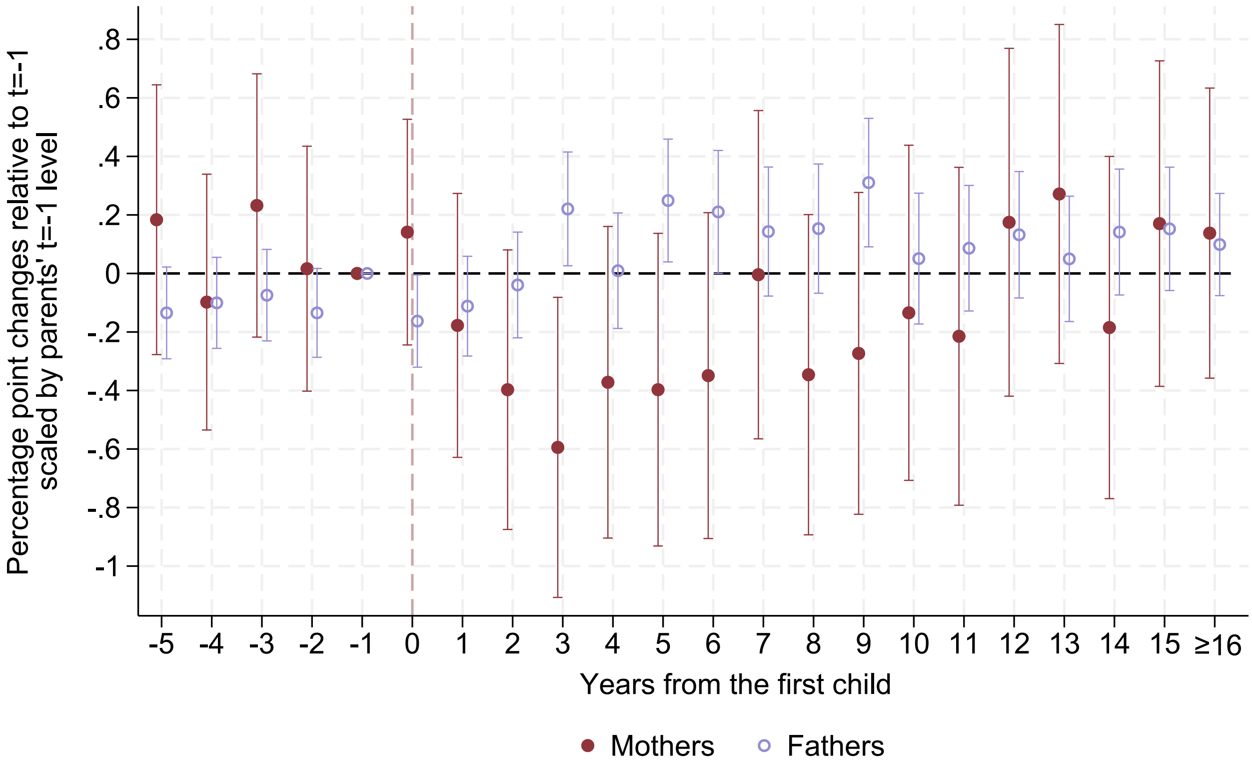


Figure A.6: Scaled Event Study Estimates from Figure A.5b: Sample Trimmed to Treatment Cohorts 1992–2004

Notes. This figure displays the dynamic DID estimates from Figure A.5b, scaled by the parents' reference year ($t = -1$) mean outcome level.

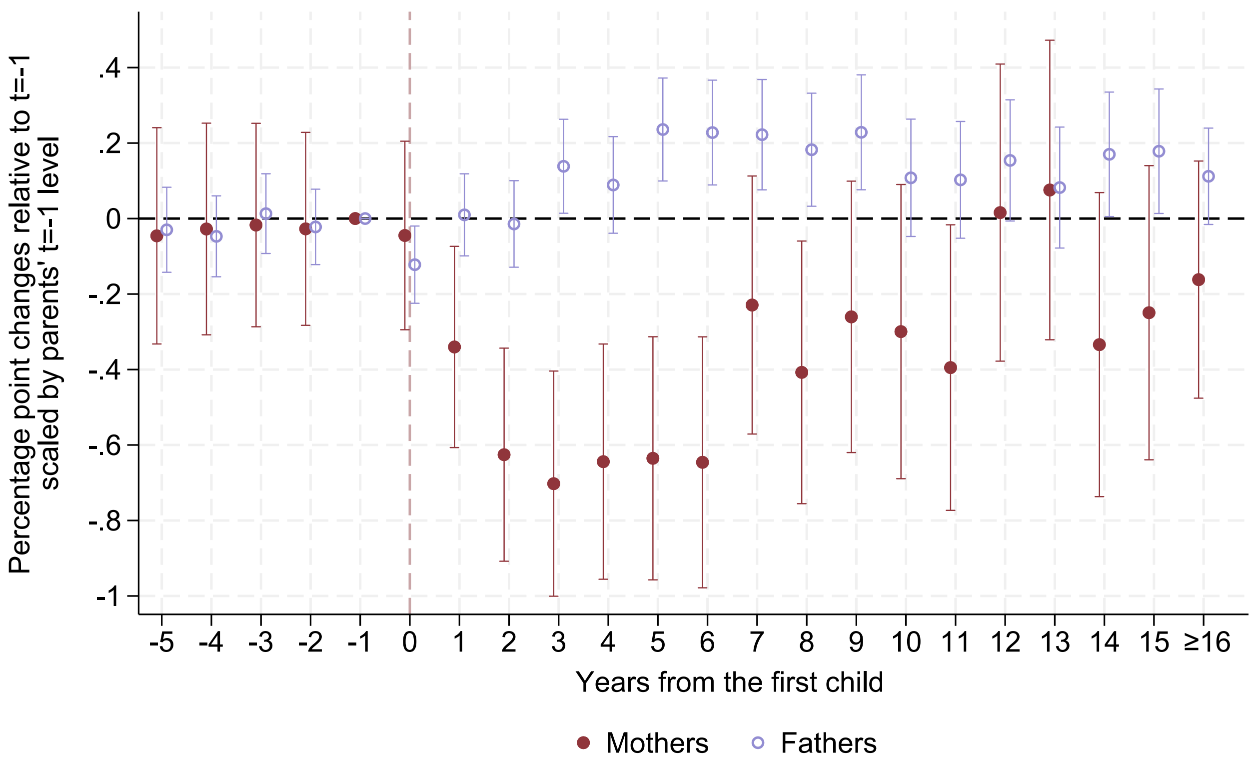
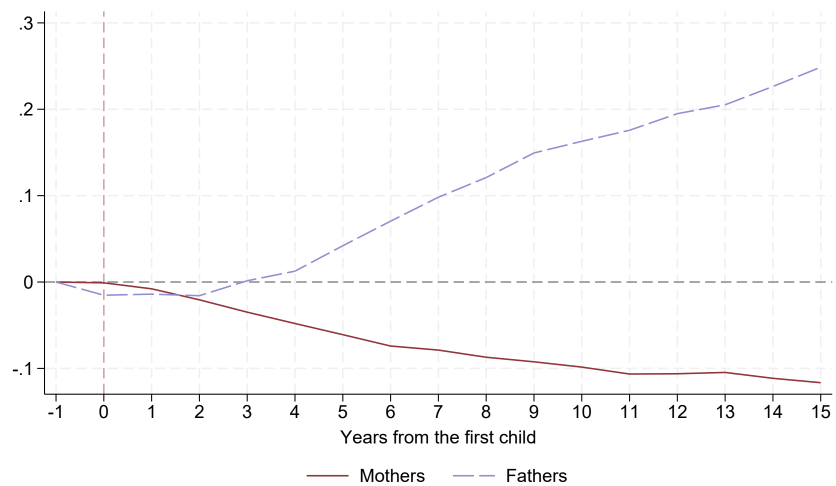


Figure A.7: Scaled Dynamic DID Estimates from Figure 3, Panel B

Notes. This figure displays the dynamic DID estimates from Figure 3, Panel B, scaled by the parents' reference year ($t = -1$) patenting rate. The outcome variable is an indicator for filing a patent application in a given year. The dynamic DID estimates are estimated separately for women and men using the model in Eq. (2). The model includes calendar year, age, and individual fixed effects. The estimation sample consists of the matched parent–childless individual pairs from cohorts born in 1950 or later, observed from 1987 to 2019. Standard errors are clustered at the individual and the matched-pair levels.

(a) Cumulative Sum of the Point Estimates in Figure 3, Panel B



(b) Cumulative Sum of the Point Estimates in Figure 3, Panel B
Scaled by Reference Year ($t = -1$) Mean Patenting Rates

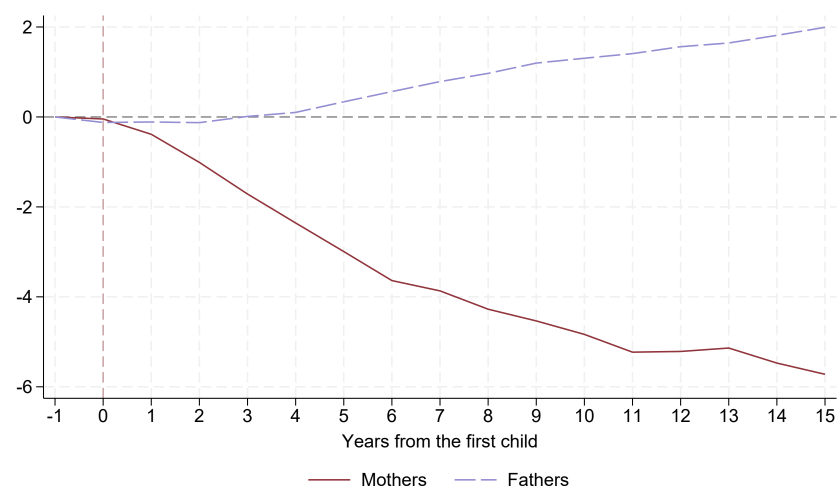


Figure A.8: Cumulative Changes in Patenting Rates Around the First Childbirth

Notes. Figure A.8a displays the cumulative sums of the point estimates in Figure 3, Panel B, reported in percentage points, illustrating the cumulative impact of parenthood on fathers' and mothers' patenting rates. Figure A.8b scales the cumulative estimates for mothers and fathers by their patenting rates in the reference period ($t = -1$).

A.6 Additional Tables

Table A.2: Top 5% Inventor-Intensive Occupations: Size and Workforce Composition

	Mean N workers	Female workers share	Male share over 50% (0/1)	Mean N inventors	Female inventors share	Any female inventors (0/1)
1. Research and development managers	4,440	0.21	1	134.7	0.07	1
2. Pharmacologists, pathologists and related professionals	256	0.68	0	7.4	0.54	1
3. Telecommunications researchers	3,561	0.14	1	90.1	0.09	1
4. Chemists	1,765	0.54	0	44.4	0.28	1
5. Electronics and telecommunications engineers	11,434	0.13	1	279.6	0.06	1
6. Chemical engineers	4,201	0.28	1	91.5	0.22	1
7. Physicists and astronomers	935	0.23	1	17.8	0.08	1
8. Information technology researchers	886	0.18	1	16.8	0.07	1
9. Telecommunications engineers	1,066	0.16	1	19.2	0.08	1
10. Mathematicians, statisticians and related professionals	29	0.47	1	0.5	0.50	1
11. Professors	2,407	0.26	1	40.7	0.09	1
12. Social science and related professionals	77	0.35	1	1.2	0	0
13. Electrical engineers	7,108	0.08	1	104.8	0.04	1
14. Mining engineers, metallurgists and related professionals	1,104	0.15	1	15.1	0.19	1
15. Physical and engineering science associate professionals	449	0.23	1	5.6	0.11	1
16. Electronics engineers	5,318	0.12	1	63.6	0.05	1
17. Health professionals (except nursing)	141	0.61	0	1.7	0.50	1
18. Rubber- and plastic-products machine operators	94	0.19	1	1.0	0	0
19. Mechanical engineers	14,881	0.07	1	157.6	0.02	1
20. Chemical engineering technicians	3,272	0.30	1	30.7	0.32	1
21. Architects, engineers and related professionals not elsewhere classified	8,662	0.20	1	72.1	0.19	1
22. Biologists, botanists, zoologists and related professionals	2,425	0.61	0	20.2	0.49	1
23. Electronics and telecommunications technicians	10,463	0.18	1	82.6	0.11	1
24. Mining and metallurgical technicians	1,130	0.19	1	8.9	0.26	1
25. Production and operations managers in manufacturing	4,698	0.08	1	35.1	0.02	1
26. Manufacturing managers	9,829	0.13	1	71.6	0.03	1
27. Electronics engineering technicians	4,070	0.17	1	28.2	0.09	1
28. Engineering professionals not elsewhere classified	8,668	0.24	1	56.9	0.12	1
29. Industrial and production engineers	4,360	0.21	1	28.1	0.10	1
30. Environmental engineers	471	0.54	0	3.0	0.26	1
31. Product and garment designers	1,338	0.57	0	7.4	0.18	1
32. Chemical and physical science technicians	305	0.45	1	1.6	0.22	1
33. Managers of small enterprises in manufacturing	1,665	0.13	1	8.6	0.01	1
34. Computer network professionals	639	0.18	1	3.3	0.04	1
35. Wood processing and chemical engineering technicians	5,915	0.23	1	29.6	0.32	1
36. Health professionals (except nursing) not elsewhere classified	633	0.84	0	3.1	0.52	1
37. Electrical engineering technicians	5,450	0.08	1	26.1	0.03	1
38. Pet producers	27	0.65	0	0.1	0	0
39. Other specialist managers not elsewhere classified	2,709	0.21	1	11.8	0.07	1
40. Policy and planning managers	1,415	0.24	1	6.0	0.11	1
41. Prosthetist-orthotists	216	0.33	1	0.9	0	0
42. Mechanical engineering technicians	17,827	0.06	1	70.9	0.03	1
43. Information and communications technology service managers	5,062	0.14	1	19.4	0.01	1
44. Assistants and part-time lecturers (university)	3,148	0.45	1	11.0	0.17	1
45. Managers of small enterprises of business services enterprises	5,847	0.27	1	20.1	0.06	1
Mean	3,787	0.28	0.82	38.9	0.15	0.91

Notes. This table extends Table 1 and displays the number of workers, the number of inventors, and the shares of women among them for the top 5% inventor-intensive occupations. The means are calculated over the years 1995, 2000, and 2004–2018.

Table A.3: Top 5% Inventor-Intensive Occupations: Gender Ranking Comparison

Occupation name	Pooled ranking	Placement in women's ranking	Placement in men's ranking
Research and development managers	1	9	3
Pharmacologists, pathologists and related professionals	2	1	1
Telecommunications researchers	3	5	4
Chemists	4	6	2
Electronics and telecommunications engineers	5	7	5
Chemical engineers	6	3	7
Physicists and astronomers	7	18	8
Information technology researchers	8	16	9
Telecommunications engineers	9	12	11
Mathematicians, statisticians and related professionals	10	2	12
Professors	11	19	10
Social science and related professionals	12	-	6
Electrical engineers	13	13	13
Mining engineers, metallurgists and related professionals	14	4	18
Physical and engineering science associate professionals	15	20	16
Electronics engineers	16	22	20
Health professionals (except nursing)	17	11	14
Rubber- and plastic-products machine operators	18	-	18
Mechanical engineers	19	27	21
Chemical engineering technicians	20	10	25
Architects, engineers and related professionals not elsewhere classified	21	14	27
Biologists, botanists, zoologists and related professionals	22	17	22
Electronics and telecommunications technicians	23	21	26
Mining and metallurgical technicians	24	8	34
Production and operations managers in manufacturing	25	35	29
Manufacturing managers	26	43	28
Electronics engineering technicians	27	23	30
Engineering professionals not elsewhere classified	28	25	31
Industrial and production engineers	29	26	33
Environmental engineers	30	28	24
Product and garment designers	31	39	23
Chemical and physical science technicians	32	33	32
Managers of small enterprises in manufacturing	33	75	38
Computer network professionals	34	48	37
Wood processing and chemical engineering technicians	35	15	53
Health professionals (except nursing) not elsewhere classified	36	29	15
Electrical engineering technicians	37	37	42
Pet producers	38	-	19
Other specialist managers not elsewhere classified	39	42	41
Policy and planning managers	40	36	43
Prosthetist-orthotists	41	-	35
Mechanical engineering technicians	42	38	55
Information and communications technology service managers	43	96	51
Assistants and part-time lecturers (university)	44	45	40
Managers of small enterprises of business services enterprises	45	61	52

Notes. This table compares the position of each top 5% inventor-intensive occupation in the pooled ranking with its respective placement in the rankings for women and men. The ranking for women is based on the ratio of female inventors to female workers, with an analogous metric applied for men. An empty cell indicates that there are no female inventors in the given occupation. The top 10 inventor-intensive occupations are highlighted in green, ranks 11–20 in yellow, and ranks 21–30 in orange.

Table A.4: Sample Sizes and Likelihood Ratios for Birth Cohorts 1962–1982 in Figure 1

	Women	Men
Full population		
N all	767,016	811,163
N inventors	1,575	10,838
Inventors per thousand	2.1	13.4
Likelihood ratio women/men	0.16	
STEM college		
N all	56,949	129,488
N inventors	1,258	8,515
Inventors per thousand	22.1	65.8
Likelihood ratio women/men	0.34	
STEM college & top 5% invent. occup.		
N all	21,146	84,031
N inventors	1,139	8,111
Inventors per thousand	53.9	96.5
Likelihood ratio women/men	0.56	
STEM college & top 5% invent. occup for 5+ years		
N all	8,461	44,138
N inventors	793	6,223
Inventors per thousand	93.7	141.0
Likelihood ratio women/men	0.66	

Notes: This table presents the sample sizes, inventor probabilities, and corresponding likelihood ratios for the full population of birth cohorts from 1962 to 1982, as well as for the three STEM college graduate subsamples shown in Figure 1.

Table A.5: Residual Gender Patenting Gap: Excluding Observations with Missing Occupation or Firm Information

	(1) Patent	(2) Patent	(3) Patent	(4) Patent	(5) Patent
Woman	-0.1180***	-0.0715***	-0.0597***	-0.0647***	-0.0575***
	(0.0022)	(0.0017)	(0.0018)	(0.0022)	(0.0020)
% of baseline coefficient in column (1) absorbed		39%	49%	45%	51%
Adj. R^2	0.0007	0.0150	0.0199	0.0306	0.0200
Observations	37,175,100	37,175,100	37,175,100	37,175,100	37,175,100
Education level × field FE	-	Yes	Yes	Yes	Yes
Occupation FE	-	-	Yes	Yes	Yes
Firm FE	-	-	-	Yes	-
High school grade FE	-	-	-	-	Yes

Notes. This table provides the estimated gender gap coefficients $\hat{\gamma}$ from five different specifications of equation (1), estimated with OLS. The estimation sample is a panel of individuals observed during the years 1995, 2000, and 2004–2018 at ages 18–65. Observations with missing firm or occupation information are excluded from the estimation sample. The dependent variable in each regression is a patenting indicator, and each specification includes indicator variables for calendar year, age, native language, and employment. Educational fields are classified at the three-digit level (ISCED-2011 compatible); educational levels are at the two-digit level (e.g., differentiating between high school and vocational secondary education). Occupations are categorized at the most detailed four-digit or five-digit level. The coefficients are multiplied by 100 for readability and therefore represent percentage point differences. The unadjusted annual probability of patenting in the sample is 0.016 percent for women and 0.136 percent for men. Standard errors are clustered at the individual level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.6: Observation Window by Treatment Cohort

Cohort	**Event Time (t)**																				
	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1988					x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1989				x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1990			x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1991		x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1992	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1993	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1994	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1995	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1996	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1997	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1998	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
1999	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
2000	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
2001	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
2002	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
2003	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
2004	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
2005	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	
2006	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x		
2007	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x			
2008	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x				
2009	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x					
2010	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x						
2011	x	x	x	x	x	x	x	x	x	x	x	x	x	x							
2012	x	x	x	x	x	x	x	x	x	x	x	x	x								
2013	x	x	x	x	x	x	x	x	x	x	x	x									
2014	x	x	x	x	x	x	x	x	x	x	x										
2015	x	x	x	x	x	x	x	x	x	x											
2016	x	x	x	x	x	x	x	x	x												
2017	x	x	x	x	x	x	x	x													
2018	x	x	x	x	x	x	x														
2019	x	x	x	x	x	x															

Notes. This table shows the observed event-time periods within the estimation window $t \in [-5, 15]$ for the 'treatment cohorts' (year of the first childbirth) from 1988 to 2019 in the panel data covering 1987 to 2019. An 'x' indicates that a given treatment cohort is observed at the corresponding event period t. Treatment cohorts 1992–2004 are observed throughout the estimation window.

Table A.7: Number of Benchmark Individual Copies in the Matched Estimation Sample

(1) Number of Copies	(2) Number of unique benchmark individuals	(3) Number of benchmark individual duplicates	(4) Total number of benchmark individuals
1	312,031	0	312,031
2	152,974	152,974	305,948
3	90,115	180,230	270,345
4	52,915	158,745	211,660
5	29,412	117,648	147,060
6	15,438	77,190	92,628
7	7,747	46,482	54,229
8	3,589	25,123	28,712
9	1,621	12,968	14,589
10	680	6,120	6,800
11	246	2,460	2,706
12	72	792	864
13	27	324	351
14	4	52	56
16	1	15	16
total	666,872	781,123	1,447,995

Notes. This table shows the number of benchmark individual copies in the matched parent-childless individual estimation sample. Column 1 categorizes the benchmark individuals by copy count; Column 2 shows the number of unique benchmark individuals in each group; Column 3 shows the number of benchmark individual duplicates in the estimation sample; and Column 4 shows the total (unique + duplicates).