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Patent Outcomes and the Gender Composition of Teams

by

Talia Bar
University of Connecticut

Heshan Zhang
PNC Bank

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365 Fairfield Way, Unit 1063
Storrs, CT 06269-1063
Phone: (860) 486-3022
Fax: (860) 486-4463
http://www.econ.uconn.edu/

Patent Outcomes and the Gender Composition of Teams

Talia Bar and Heshan Zhang[1]

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Abstract:

We examine gender differences in US patent outcomes -- forward citations, triadic grants (related patents in EU and Japan), and renewals. We find that differences in workplace explain a significant part of the gap. After accounting for technology, application years, examiners and patent assignees, we show that while on average, patent teams with at least one woman-inventor have slightly weaker outcomes, for solo-inventor patents there are no significant gender differences in any of the outcomes. But men-lead mixed gender teams have on average slightly weaker outcomes than men-only teams, even when we control for the identity of the first inventor.

[1] Talia Bar. Email: talia.bar@uconn.edu. University of Connecticut, Department of Economics. 335 Susan V. Herbst Hall. Phone: 860-4863550. Heshan Zhang. Email heshanzhang62@gmail.com. PNC bank. An earlier version of this paper was part of Heshan's dissertation. We are grateful to Jorge Agüero, Haim Bar, Delia Furtado, Tom Miceli, Steve Ross, and workshop participants for helpful comments and suggestions. We thank Faifan Wang for research assistance, and the University of Connecticut CLAS for Summer 2023 funding.

Introduction

In recent years, there is heightened awareness of women's low participation in patenting. The share of U.S. inventors receiving patents who are women is only about 13 percent (USPTO, 2020).[2] Increasing women's participation in innovation activities seems to have become a priority for the USPTO. Similarly, the World Intellectual Property Organization (2021) reports that in 2020 only 16.5 percent of inventors in international patent applications were women, and that "WIPO is actively working towards gender equality". Broader participation in innovation might benefit and empower women and promote economic growth (Giczy, Pairolero, and Toole, 2024; Hunt et al., 2013). Learning more about which environments are most conducive to women's participation in successful R&D teams is key to narrowing the gender gap in patenting.

We examine differences in outcomes for all-male-inventor patents, and patents that have at least one female inventor, and consider possible sources for these differences. We use three outcome measures that are often used as different indicators of patent success. All three measures are argued to be associated with economic value, but measure different aspects of success: (i) Forward citations proxies for the technological significance (Trajtenberg, 1990, Squicciarini, et al. 2013) and influence on future inventors. (ii) "Triadic grants"—have patents in the same family granted also in the Japanese and European patent offices, indicates high quality in terms of the likelihood of validity (de Rassenfosse et al. 2020; Frakes and Wasserman 2017), because these inventions met the patenting criteria of three patent offices. (iii) Payments of the fourth-year renewal fees indicates continued promise for profitability (Pakes, 1986).

We utilize a large and rich dataset of USPTO utility patents granted between 2000 and 2018. To construct our dataset, we combined multiple USPTO datasets on patent inventors, patent applications, and maintenance fee events, and the OECD 2023 datasets of patent indicators and triadic grants. Controlling for technology fields and application years, like in earlier studies (Jensen et al., 2018; Hochberg et al., 2023), we observe that patents with a female inventor have on average fewer forward citations. We additionally show that patents with a female inventor are, on average, less likely to be classified as "triadic grants" and less likely to be renewed after four years.

Companies differ in workplace flexibility, in opportunities for collaborative work, organization structure, benefits, their dealing with microaggressions etc. (Field et al., 2023) and

[2] See https://www.uspto.gov/about-us/news-updates/uspto-releases-updated-study-participation-women-us-innovation-economy-0

these can affect women's representation and roles. A gap in patent outcomes (after controlling for technology fields and application years) could originate from gender differences in selection into not only technology fields but also employers within fields. Average patent outcomes also differ by organization for several reasons including company-specific technologies, intellectual property related strategies, R&D resources, and access to legal support. We find that patent assignees (often the company or institution where inventors work) explain a large part of the gender gap in patent outcomes. It accounts for 33% of the gap in citations, 29% of the gap in triadic grants and 76% of the gap in four-year patent renewals. Still, even within assignees, patents with at least one female inventor have on average worse outcomes.

The magnitudes of the gender gaps in patent citations and triadic grants are further narrowed when we add patent attributes to the model (after controlling for technology field, assignee and examiner), suggesting differences in patent attributes explain at least in part the gender gap in these patent outcomes. Examining sensitivity of the coefficient of interest to the addition of observed patent attributes (Oster, 1999), suggests that the gender gap within technology fields and assignees for these outcomes could plausibly be explained by differences between the attributes of patents that have at least one female inventor and those with all male inventors. The gap in the patent renewals outcome is small but remains stable when adding observed patent attributes.

If women receive fewer R&D resources than men in their workplace, this might result in weaker patents and lead to differences in patent outcomes. A gap in outcomes could also arise if otherwise identical patents are later less likely to be cited, granted in other offices, or renewed when there is a women inventor in the team. This might be the case if parties (e.g., inventors, lawyers, examiners, or company executives) treat women-inventor patents differently than men-inventor patents, or if after grant women inventors behave differently than men inventors, say are less likely to promote their own inventions, which leads to different outcomes. If either of these explanations is the main driver of the gender gap in outcomes, we would expect to see a gender gap when comparing patents of single male inventors with patents of single female inventors. Interestingly, for solo inventors the differences in outcomes are small and insignificant. With these explanations we might also expect a larger gap between same gender teams than between mixed gender teams and all male teams, but that is not the case.

It has been suggested that team composition can affect performance. Evidence on the effects of gender diversity on team productivity is mixed (see for example Kim and Starks, 2016 in the context of board members and Azmat, 2019 for a survey of related literature). We find a gap in outcomes when comparing mixed gender teams relative to men-only teams. Restricting the sample to patents that have a male first-inventor and at least one other coinventor, we find that even when we control for the identity of the first inventor, patents that include at least one female inventor have weaker outcomes than those with only men co-inventors. Taken together the evidence seems consistent with either worse performance of mixed gender team, or with mixed gender teams working on less promising projects.

This study mainly relates to the recent literature on the role of gender in patenting. Using Kogan et al. (2017) stock-market based measure of economic value, Giczy, Pairolero, and Toole (2024) find that gender balanced teams in Artificial Intelligence patents have higher patent values. Subramani and Saksena (2024) find that patents by majority female inventors are less likely to be further developed and they receive fewer citations than majority male inventor patents. Aneja et al. (2024) used an instrumental variable approach (based on examiner strictness) to show that women are less likely to continue in the application process following an early-stage rejection. Jensen et al. (2018) found that women inventor's applications are more likely to be rejected and they are less likely to appeal these rejections. Hochberg et al. (2023) use machine learning techniques to find that female lead inventors are under-cited.

Data

We put together a rich dataset of utility patents that were granted by the USPTO in 2000-2018. We first append Annualized Data Tables from PatentsView (provided by USPTO Office of the Chief Economist).[3] This dataset includes the assignee(s) of the patent (usually companies) and the gender of up to 9 patent inventors. Gender in the USPTO dataset was generated using a gender attribution algorithm because inventors do not need to state their gender when applying for a patent.

We restrict the dataset to US assignees and keep one observation per patent. For patents with multiple assignees, we kept the name of the most prolific assignee. Only about 2% of the

[3] See https://patentsview.org/data/annualized

utility patents had multiple assignees. We constructed a dummy variable that equals 1 if a patent had more than one assignee and 0 otherwise, so we can control for multi-assignee patents in our models. We also restrict to patents with at most 9 inventors (more than 99% of the patents), and exclude those with missing gender information, resulting in a loss of about 13% of the patents. Our main results are robust to keeping all patents with at least one inventor who has a gender attribution.

We merge these data with an applications dataset from the USPTO's PatEx that includes application dates, technology classifications and examiner art unit and name.[4] There are over 800 different art units. Less than 0.2% of the observations were missing examiner art unit. Art units capture information about the patent's technology field. Examiners can influence the quality of patents by adding backwards citations or limiting the scope of claims. Examiners might also specialize in certain technologies even within art unit (Righi and Simco (2017)) and different technologies could have different participation of women and different outcomes. We group art-unit by examiner name to control for possible effects of examiners on outcomes. Additionally, we construct a time varying examiner experience variable using the count of previous examiner patents. To construct this variable, we use all the years in the examination dataset, and count earlier patents for the same examiner in the same art.

To control for inventor experience, we reshape the dataset that includes patents granted from 1976 to the inventor level. We then create a variable that counts the number of previous patents by the patent's lead inventor, as well as a variable that equals to the average number of patents held by the team's inventors. We merge these variables back into the patent level data.

We parsed the title of each patent, and identified the following frequently used terms that appear in patent titles "method", "system", "process", "apparatus", "device". We create a dummy variable for each of these words to capture information about the invention.

We augment the USPTO data sources by merging with The Patent Quality Indicators database (OECD, 2023) that provides a 5-year (from publication) forwards citation count (or 7-year). This is the source of our first outcome variable of interest – forward citations. This dataset

[4] https://www.uspto.gov/ip-policy/economic-research/research-datasets/patent-examination-research-dataset-public-pair

also provides us with patent attributes that could capture the patent's potential for success (according to one of our measures), including the number of claims, backwards citations, citations to non-patent literature, grant lag, and patent scope (based on technology classifications).

For our second outcome of interest, we merge our data with the Triadic Patent Families (TPF) database (OECD, 2023). This database allows us to construct the triadic-grant indicator. Triadic grant is equal to 1 if the US granted patent in our primary dataset has in its family also an EPO granted patent and a JPO granted patent. We defined this variable to equal 0 otherwise (either if no EPO or JPO patent was applied for, or if there was an application but no grant).

Our third outcome is a 4-year renewals indicator. To keep a US utility patent in force, the owner is required to pay maintenance fees prior to years 4, 8 and 12 after the date of issue.[5] We add to our dataset an indicator that we construct using the USPTO patents maintenance fee events data.[6] The renewals indicator is equal to 1 if the 4th-year maintenance fees were paid to renew the patent and 0 otherwise.

All three outcomes can indicate a patent's economic value. But they also capture different aspects of success, are determined at different times, and might be influenced by different decision makers. Simple unconditional correlations between the three measures are low: 0.15 between triadic grants and forward citations, 0.07 between triadic grants and renewals, and 0.03 between renewals and forward citations.

To capture the gender composition of patent teams, our main variable of interest is a dummy variable "has female" that is equal to 1 if one of the patent inventors is a woman inventor, and 0 if all the inventors are men. Thus, we compare patent outcomes of teams with at least one woman-inventor to those with all men inventors. We alternatively include separate indicators for all female, or mixed gender patents. Alternatively, we measure the gender composition of patent teams with the share of the patent inventors who are women.

We use US patent classes as a control for the patents' technology area. Our data includes 434 patent classes. Examiner art unit by examiner name fixed effects provide further detailed

[5] https://www.uspto.gov/p0atents/maintain
[6] https://developer.uspto.gov/product/patent-maintenance-fee-events-and-description-files

control for the technology area of the patent. Figure 1 illustrates technology field variability in the share of patents that have at least one female inventor using a coarser field classification from the OECD dataset. The share of patents with at least one female inventor ranges from 9% in the Mechanical Elements technology field, to 49% in Biotechnology.

For many of the observations, the assignees are large companies. We restrict the sample to assignees with more than one patent, dropping 3.7% of patent observations that had an assignee with only one patent. These observations would be dropped when estimating models with assignee fixed effects. The resulting dataset has over 1.5 million patent level observations. There are more than 58,000 assignees. The distribution of the number of patents per assignee is skewed. In our sample, the company with the most patents is International Business Machines (IBM), with more than 80,000 patents during our sample period. In total, the largest five companies hold about 10% of the patents. Half of the patents in our sample are assigned to assignees that have 744 or more patents. Figure 2 shows the share of patents that have at least one female inventor in different sub-samples of assignees. In the subsample of university or college assignees 35% of the patents have at least one female inventor, compared with only about 20% for companies.

Table 1 describes the data. In the first 2 columns we use all the observations, and split the sample to observations of patents with at least one woman-inventor (19%), and those with all men inventors. The average number of inventors in patents with at least one woman-inventor is 3.64, and in all male patents the average team size is 2.36. The next two columns describe the solo inventor subsample of patents. Only 5.4% of the patents that only have one inventor were invented by women inventors. The table shows the averages and standard deviation of the outcome variables and patent attributes.

On average, patents receive about 19 citations, about 12 percent of patents by all male inventors have triadic grants, and about 16 percent of patents have at least one woman-inventor, about 90% of patents are renewed at the 4-year mark. In the solo inventors' sample, patents invented by a women inventor have about 14 compared with about 16 for the ones by male solo inventor. About 10 percent of solo patents have triadic grants and about 90 percent of solo patents are renewed for at least four years. The descriptive table does not account technology field, application year, patent size or assignees which are important determinants of patent outcomes.

The attributes of patents with at least one female inventor are on average different from those with only male inventers, the differences are in most cases statistically significant but small in magnitude. Notably, the first inventors of patents with at least one female inventor are on average less experienced (measured by the count of previous patents) that than the first inventor in all male patents, and the average experience of the team is also lower. In the solo sample, female inventor patents have fewer patent claims and fewer backwards citations, but more non-patent literature citations than male inventor patents.

Empirical Strategy

We compare differences in three patent outcomes – forward citations, triadic-grants and renewals – between patents with only men inventors and patents with at least one woman-inventor. Women's participation in patenting varies by technology fields and over time, and there are differences in outcomes across fields. In all the models we include either technology field by application year fixed effects to control for these differences. Women tend to participate in larger teams and outcomes might depend on team size. Therefore, we include a dummy variable for each team size. In the baseline model we estimate for patent *i*, in field *f* and application year *t*:

$$Y_{ift} = \beta_0 + \beta_1 has\_female_i + \boldsymbol{\beta}_2 \cdot \boldsymbol{team\_size}_i + v_{ft} + \varepsilon_{ift} \, . \qquad (1)$$

The dependent variable *Y* is one of the three patent-outcomes, has_feamle is the gender composition variable of interest. It is equal to 1 if the patent has at least one female inventor. The vector **team_size** includes dummy variables for each number of coinventors in a team 2-9, v_{ft} are field by application year fixed effects. If $\beta_1 < 0$, patents with at least one female inventor are on average less successful according to the measure *Y*.

Companies, institutions or other organizations where inventions take place differ in the specific technologies they develop, the resources they allocate to R&D, their intellectual property strategy, their legal teams, work environments etc. These differences can lead to differences in patent outcomes. We account for gender differences in inventors' workplace by including patent assignee fixed effects, α_j. The assignee is the patent owner, which is often the company or institution where inventors work. A decline in the magnitude of β_1 would suggest that differences in inventors' workplace explain at least in part the observed differences in outcomes.

Examiners and their art units also capture technology specialization. Righi and Simco (2017) find "strong evidence that examiners specialize in particular technologies, even within relatively homogeneous art units." Additionally, examiners help shape the patent through their choices of prior art citations, the stringency of their patent review, and the changes they request to the number and scope of the patent claims. Thus, examiners can influence patent outcomes. We add art unit by examiner name fixed effects to the model to capture the effects of the patent examiner on patent outcomes. We also add the examiner's number of previous patents (to measure of the examiner's experience).

Our data includes several observed patent attributes that may predict outcomes: the number of patent claims, backwards citations, citations to non-patent literature, grant lag, patent scope, and the first inventor's experience (proxied by the number of previous patents). All of these attributes are determined either before patent application or during patent prosecution and generally remain fixed after patent grant.[7]

We gradually add to the model in (1) assignee fixed effects α_j, then examiner art unit by examiner fixed effects ξ_i and then our list of patent attributes $\mathbf{X}_i$ which include those listed above and the squares of the continuous control variables to obtain the following model:

$$Y_{iftj} = \beta_0 + \beta_1 has\_female_i + \boldsymbol{\beta}_2 \cdot \boldsymbol{team\_size}_i + \boldsymbol{\beta}_3 \cdot \mathbf{X}_i + v_{ft} + \alpha_j + \xi_i + \varepsilon_i \quad (2)$$

A change in β_1 after adding patent attributes $\mathbf{X}_i$ to the model with assignee fixed effects suggests that the patents invented by teams with at least one woman are different, and these differences lead to different outcomes. If β_1<0 in the model with fixed effects, and it increases (decreases in magnitude, or changes sign) when we add patent attributes, it suggests that worse patent outcomes for teams with at least one woman-inventor are likely explained at least in part by these patents being weaker (in the sense of potential to be cited, granted in other offices or renewed).

[7] Patent reexamination or patent reviews could result in changes in claims after grant but these are fairly rare events and are not captured in our data.

Had we been able to perfectly control for patent attributes that can lead to outcome differences, then β_1 in equation (2) would capture gender differences in patent outcomes that occur after patent grant. For example, those that might result if future inventors or examiners are less inclined to cite patents with women inventors, or if women inventors are less likely to promote their own work. However, while the data is rich, there are likely still omitted unobserved attributes that bias this coefficient.

Oster (1999) developed a method that uses movements in the regression coefficients and in the R-squared to obtain a bound on the effects of unobserved variables, assuming that selection on observables is informative. Comparing model (2) to the same model that does not include observed patent attributes $\mathbf{X}_i$, we use her method to estimate a bound on the coefficient of has female. Using $\delta = 1$ as the relative degree of selection on unobservables to selection on observables the estimate of the bound is given by:

$\beta^* = \beta_1 - (\beta_1^0 - \beta_1)\frac{R_{max}-\tilde{R}}{\tilde{R}-R^0}$ where β_1 and β_1^0 are the coefficients of *has_female* with and without including observed patent attributes and $\tilde{R}$ and R^0 are the R-squares in these models and and $R_{max} = 1.3\tilde{R}$ is taken to be the maximum R square if we could observe all the attributes that predict outcomes. If $\beta_1 < 0$ in our full model, and β^*<0, it would offer some support for a gender gap even for otherwise identical patents. If $\beta_1 < 0$ in our full model, and β^*>0, then the negative difference is not robust and it is likely explained by unobserved patent attributes.

Two potential explanations for a gender gap in outcomes after controlling for technology, examiners and assignees are: (1) women are disadvantaged in their workplace, getting access to fewer R&D resources or (2) women are disadvantaged after patent grant either because of the behavior of others (e.g., examiners or inventors of future patents might be less inclined to cite patents with women inventors), or of inventors themselves, (e.g., men might be more likely to promote their own inventions). If one of these explanations were the main driver of the gender gap, we would expect to see a gender gap when comparing the outcomes of patents invented by solo women inventors with the outcomes of patents of solo men inventors. We would also expect a bigger gap between same gender teams than between mixed gender teams or men only teams. We therefore estimate the models described above for the subsample of solo inventors, or for the full sample, replacing the *has_female* indicator with two variables, one for all female teams and one for mixed gender teams.

A third possible driver for a gender gap could be differences in productivity of diverse teams. Empirical evidence on the effects of gender diversity of teams' productivity is mixed. Worse outcomes for teams with a female inventors could be a result of worse performance of mixed gender diversity in teams. If this drives the observed weaker outcomes of teams with at least one female inventor, then in the models above we would not expect to see gender differences in the solo subsample, and we would expect to see a negative coefficient on the mixed gender team indicator.

There is no difference in the legal rights of the first coinventor listed on a patent and the other coinventors. In practice, however, often the first inventor is the inventor who played the most significant role in the invention, or a lead role.[8] Sometimes only the first inventor's name is used when referencing a patent, so being first can matter to inventors. For the assignee, choosing a well-known inventor might add value to the patent. Women are especially underrepresented as lead inventors. If there are differences in specific technology areas, or resources that would lead to differences in patent outcomes for different lead inventors, and some lead inventors are more likely to collaborate with women than others, this can lead to a correlation between patent outcomes and the gender composition of the patent. We therefore also estimate models with first inventor fixed effects restricting to the sample of patents with male (or female) first inventors. This allows us to see differences between outcomes of patents of the same lead inventor when he/she collaborates with same gender times versus mixed gender teams.

To gain insight on types of assignees where the gender gap is more pronounced, we partition assignees into seven groups, to distinguish different types of assignees. We used string operations on the name of the assignee names to classify assignees, making sure each assignee belongs to one and only one group. We made some corrections to the initial classification based on inspection of assignee names for prolific assignees. It is possible that in some cases the classification is imperfect. The groups we define include (i) institutions of higher education (mostly those with university, college, school, and institute of technology in their assignee names;

[8] See https://thompsonpatentlaw.com/named-first-on-a-patent/ and https://www.upcounsel.com/patent-inventor-name-order . Last accessed March 13, 2024.

(ii) the US government or US departments; (iii) institutions and foundations including hospitals and medical research centers, but excluding those that were included in the education group; (iv)-(vii) companies are the remaining patent assignees and we split them into four groups, based on whether they have above or below median numbers of patents and on whether the share of female inventors in the assignee is above or below the median share of female inventors.

Results

In Table 2 we compared the outcomes of patents that have at least one woman-inventor with the outcomes of patents that have only men inventors. We use here our full sample of patents. Each panel shows regressions with a different dependent variable: in Panel A, five-year forward citations; in Panel B, triadic grants; in Panel C four-year patent renewals. In each Panel, column (1) shows estimates of a baseline model that controls only for patent class by application year fixed effects (as an indicator of the invention's technology field) and team size. In column (2) we add to the model assignee fixed effects (likely representing the company or institution where the inventor works). In column (3) we add examiner fixed effects, and the time varying examiner experience variable. In column (4) we add observed patent attributes.

In the bassline specification in column (1) of each panel, patents with at least one woman-inventor have worse outcomes according to our three measures. These patents have on average about 3.6 fewer 5-year citations, are about 1.8 percentage points less likely to have a triadic grant, and about 1.3 percentage points less likely to be renewed after four years. When adding assignee fixed effects in column (2) we see that the magnitudes of the coefficients drop by 33% for forward citations, 29% for triadic grants and 76% for patent renewals. This suggests that patent assignees (often the company or organization where patent inventions take place) explain a large portion of the observed gender gap in outcomes. The coefficient remains negative, suggesting that even within assignees, patents with at least one woman-inventor, on average, fare worse.

In column (3) we add examiner art unit by examiner name fixed effects and the variable capturing the examiner's experience. This results in a minor decline in the coefficient of interest for the first two outcomes, and a 25% decline in the coefficient for patent renewals. It is possible that differences in examiner specialization (between and within art units) explain this change.

In column (4) we add patent attributes variables that we expect could be associated with the patent's "potential" to be cited, granted in three offices, or renewed. Adding patent attributes further attenuates the coefficient β_1 of *has_female*. Thus, gender differences in patent attributes that are known at the time the patents are granted explain, at least in part, the gender gap in patent outcomes. The coefficients β_1 in column (4), remain negative and statistically significant but are now quite small. The narrowing of the gender gap in forward citations and triadic grants when we include patent controls that predict these outcomes suggests that, conditional on assignee, examiner and team size, patents with at least one female inventor have attributes that make them less likely to gain citations and triadic grants, so that the gender gap showing weaker outcomes for patents with a female inventor seems wider when they are excluded. The coefficient in the patent renewals model remains stable, indicating that observed patent attributes do not have much power to predict patent renewals.

Our controls are unlikely to fully capture patents' potential for success. There could be omitted patent attributes that predict outcomes and correlate with the gender composition of the team. We report Oster's (2019) bound β^* for the coefficient of *has_female* at the bottom of each panel in table 2, assuming that omitted patent attributes are proportional to observed ones. We compute this estimate using the coefficients and R square values for the model in column (4), (which includes the fixed effects and observed patent attributes), relative to the model in column (3) that includes the fixed effects but does not include patent attributes. The bound is small and positive for citations and triadic grant outcomes. Thus, once we condition for assignee, examiner and team size, the existence of a gender gap is not robust. There could be omitted patent attributes that if added would close the gender gap in forward citations and triadic grants even if they are less important than observed patent attributes. The coefficient in the patent renewals model in panel C is stable when adding patent attributes.

In Table 3 we repeat the full models from Table 2 restricting to the sub-sample of patents with solo inventors. While the baseline specification that only controls for patent class fixed effects and team size shows a gender gap of about 2.6 forward citations, 1.2 percentage point lower probability of triadic grant and 0.8 percentage points in renewals, as soon as we add assignee fixed effects in column (2) the coefficient of *has_female* drops in magnitude to -0.04 citations, and become statistically insignificant, the gap in triadic grants and renewals also drops in magnitude and is statistically insignificant. In the full model in column (4), where we include all fixed effects and controls, we find no significant gender gap in patent outcomes. The sign flips for the forward-citations outcome but is insignificant and the coefficients remain small, negative and insignificant for triadic grants and renewals.

No significant gender differences in outcomes for solo inventors could be consistent with women being under-cited or less likely to be granted triadic grants or have their patents renewed if solo women inventors had stronger patents than men solo inventors. But the direction of change in the coefficient when adding patent attributes in the forward citations or triadic grant models does not support this. The *has_female* coefficient increases becoming positive (insignificant) or negative but closer to zero when we add patent controls. For the renewal's outcome, the inclusion of patent attributes leads to a small decrease in the coefficient of *has_female*, but the coefficient is small and insignificant whether or not we add patent attributes. The findings in table 3 do not lend support to hypotheses that suggest that the gender gap is created due to ex-post factors such as future inventors or examiners treating women patents less favorably, nor to the hypothesis that the gap is driven by fewer resources allocated to women inventors within the workplace. Because in these cases we would expect to see a significant gap between solo female inventors and solo male after controlling for assignee fixed effects.

In Table 4, we compare the outcomes of mixed gender teams, and same gender teams. A mixed gender team has at least one male inventor and at least one female inventor. In panel A, for each outcome we estimate the model with class by year, assignee, and art unit by examiner fixed effects and controls (as in column 4 of Table 2), but we replace the *has_female* indicator with two dummy variables, one for women only teams and one for mixed gender teams. The coefficient of mixed gender teams is negative and significant. The coefficient of women only teams is noisy. It is positive and insignificant for forward citations, negative and marginally significant for triadic grants, negative insignificant for renewals. We note that the share of women only teams is small. Only 2% of all patents have only female inventors and 89% of these patents have a solo inventor.

In Table 4 Panel B we restrict the sample to teams with at least two inventors. For each outcome, we estimate the model with first-inventor fixed effects. We include the indicator for mixed gender teams, and its interaction with a dummy for a female first inventor. The coefficient is now estimated from variation of gender composition of the team (mixed or same gender) for the same lead inventor. For men first inventors, patent outcomes are worse when they have a mixed gender team. The interaction of mixed gender with a female first inventor indicator is positive but insignificant and the sum of the main effect and interaction is also insignificant. Thus, we cannot conclusively compare mixed and same gender teams for female lead inventors.

We consider heterogeneity of the gender gap for different groups of assignees. In the models presented in Table 5, we interacted the *has_female* indicator with each of seven groups of assignees: education, institutes and foundations, government, and companies split to four group according to their number of patents and share of female inventors (above or below median). For most groups of assignees and outcomes there is a negative coefficient for the interaction of the group with has female – i.e. in most groups patents with at least one women inventor have weaker outcomes. The only positive coefficient that is marginally significant is that of the government assignees in the renewal's outcome. The magnitude of the gap in citations is relatively larger in the education assignees and in the "institutes and foundations" group of assignees. Focusing on companies, the gender gap in outcomes is larger in magnitude for the group of assignees that has below median number of patents and a low share of female inventors than in the group that has above median number of patents and a high share of female inventors. The difference is statistically significant for the first two outcomes, but not for patent renewals.

We show robustness of our results with a number of additional tests in the Supplemental Appendix. These include: (i) Longer-term outcomes, 7-year forward citations, and 8-year patent renewals (for patents granted in 2000-2014). See Tables A1-1 and A1-2. (ii) Replacing the *has_female* patent composition variable of interest with the share of female inventors in the patent or with the gender of the first inventor. See Tables A2-1 and A2-2. (iii) Using a larger dataset that includes all patents with at least one observed inventor's gender. See Table A3.

Conclusion

Our paper considers the association between the gender composition of patent teams and three patent outcomes: forward citations, triadic grants and patent renewals. Consistent with earlier studies, we find patents with at least one female inventor have weaker outcomes on average. We highlight the importance of inventors' workplace. There are gender differences in where women work and invent. Companies and organizations have different business strategies, R&D resources, etc. Controlling for patent assignees substantially narrows the patent outcomes gender gap.

We find no significant gender differences in outcomes for solo inventors (after controlling for patent assignees), nor for same gender inventor teams. Instead, there is a gap in outcomes for mixed gender teams relative to men only teams.

These patterns do not seem to offer support for ex-post gender differences (e.g. future inventors being less likely to cite women inventors), nor differences in resources allocated to women versus men inventors within firms. Because in such cases we would expect to see a significant gap between solo women and solo men inventors, which we do not. Thus, a proposal to conceal the identity of patent inventors (Jensen et al., 2018) might not help narrow the gender gap in outcomes.

Given our findings, it seems plausible that within companies' either women select (by choice or assignment) into male lead teams that work on less promising projects or that mixed gender teams produce somewhat weaker patents. Awareness of the observation that within companies, mixed gender teams do not do as well as men only teams would hopefully lead relevant decision makers to pay attention to whether there are differences in the assignments of projects to mix gender teams, or differences in the dynamics within teams when men lead mixed gender teams compared with all men teams.

The share of women among patent inventors is still low but slowly growing. Turban, Wu, and Zhang (2019), suggest that "gender diversity relates to more productive companies … only in contexts where gender diversity is viewed as "normatively" accepted". We have found that at least a third of the gender gap in outcomes is explained by patent assignees, and so the work environment seems to matter. The gap is larger for some types of assignees. For the forward citations' outcome, patents with at least one female inventor seem to have particularly weaker patents in higher education and in institutions and foundations, while the gap is smaller in companies. No significant gender gap for any of the outcomes is seen in the case of companies with below median number of patents and a high share of female inventors. Policies that promote women participation in STEM occupations and in patenting and that promote a positive atmosphere for women in the workplace might help narrow or eliminate the gap in outcomes.

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Table 1: Summary statistics by gender composition

	Any Team Size		Solo Inventor		
Gender Composition	Has female	Male only	Female	Male	Test solo
Outcome					
Forward Citations (5y)	19.714 (64.111)	19.091 (64.551)	13.708 (39.147)	15.769 (58.690)	<0.001
Triadic Grants	0.163 (0.369)	0.123 (0.329)	0.101 (0.302)	0.097 (0.295)	0.017
Renewals (4y)	0.879 (0.326)	0.897 (0.304)	0.887 (0.316)	0.896 (0.306)	<0.001
Characteristics					
First inventor experience	18.883 (49.005)	20.536 (51.286)	12.971 (24.393)	20.428 (53.271)	<0.001
Mean experience	16.439 (34.597)	18.926 (43.207)	12.971 (24.393)	20.428 (53.271)	<0.001
Claims	19.459 (12.911)	19.769 (12.809)	18.806 (12.649)	19.286 (12.227)	<0.001
Backward Citations	33.210 (80.780)	33.483 (83.716)	26.431 (49.528)	29.156 (59.891)	<0.001
Non-Patent Citations	12.976 (31.236)	8.083 (24.665)	9.083 (25.142)	6.475 (20.283)	<0.001
Patent Scope	2.130 (1.374)	1.940 (1.228)	1.971 (1.275)	1.883 (1.188)	<0.001
Grant Lag	3.221 (1.782)	3.082 (1.712)	3.136 (1.740)	3.026 (1.691)	<0.001
Examiner Experience	117.757 (129.663)	122.014 (138.215)	116.173 (126.197)	121.090 (136.513)	<0.001
Method	0.329 (0.470)	0.324 (0.468)	0.324 (0.468)	0.320 (0.466)	0.165
System	0.195 (0.396)	0.233 (0.423)	0.195 (0.396)	0.226 (0.418)	<0.001
Process	0.050 (0.218)	0.045 (0.207)	0.044 (0.206)	0.039 (0.192)	<0.001
Apparatus	0.069 (0.253)	0.096 (0.295)	0.073 (0.260)	0.098 (0.297)	<0.001
Device	0.080 (0.272)	0.091 (0.287)	0.084 (0.277)	0.090 (0.286)	0.002
Multi-assignee	0.035 (0.184)	0.016 (0.127)	0.012 (0.108)	0.009 (0.093)	<0.001
Team Size	3.642 (1.791)	2.358 (1.425)	1	1	
Observations	296,933 (19.0%)	1,263,913 (81.0%)	24,110 (5.4%)	424,335 (94.6%)	

Notes: Summary of dependent variables and patent attributes for all team sizes combined (in the first two columns) and for solo inventors in the next two columns. The table shows mean(sd) for patents with at least one female and for patents with only male inventors. The last column shows t-tests between female and male inventors for the solo inventor sample.

Table 2: Patent outcome and the gender composition of teams

	(1)	(2)	(3)	(4)	
VARIABLES	class-year	Assignee	Examiner	Controls	
	Panel A - Forward Citations (5-year)				
has_female	-3.6384***	-2.4516***	-2.3296***	-1.3545***	β*=1.9397
	(0.2508)	(0.4389)	(0.4150)	(0.3644)	
Observation	1,555,846	1,555,718	1,553,166	1,553,161	
R-squared	0.0697	0.2845	0.3222	0.3536	
	Panel B - Triadic Grants				
has_female	-0.0178***	-0.0127***	-0.0126***	-0.0087***	β*= 0.0148
	(0.0012)	(0.0019)	(0.0018)	(0.0016)	
Observation	1,557,161	1,557,063	1,554,502	1,553,032	
R-squared	0.1004	0.3114	0.3336	0.3511	
	Panel C - Renewals (4- year)				
has_female	-0.0132***	-0.0032***	-0.0024**	-0.0024***	β*=-0.0024
	(0.0009)	(0.0011)	(0.0009)	(0.0009)	
Observation	1,556,892	1,556,783	1,554,222	1,552,752	
R-squared	0.0279	0.2221	0.2728	0.2741	
Team size	YES	YES	YES	YES	
Class by year	YES	YES	YES	YES	
Assignee	NO	YES	YES	YES	
Examiner	NO	NO	YES	YES	
Controls	NO	NO	NO	YES	

Notes: All models are estimated using linear high dimensional fixed effects models (Stata's reghdfe). All models include patent class by application year fixed effects and team size dummies. We gradually add assignee fixed effects in column (2), art unit by examiner fixed effects and examiner experience in column (3) and patent attributes in column (4). In each column, we cluster standard errors at the fixed effects levels. In the last column we report Oster's β* for δ=1 and Rmax=1.3 times the full model R-squared, using column (3) as the reference point.

Table 3: Patent outcome and the gender of solo patent inventors

	(1)	(2)	(3)	(4)
VARIABLES	class-year	Assignee	Examiner	Controls
	Panel A - Forward Citations (5-year)			
has_female	-2.6025***	-0.0381	-0.2106	0.3808
	(0.5758)	(1.0379)	(0.6771)	(0.6316)
Observations	446,398	437,263	434,046	434,044
R-squared	0.0602	0.4169	0.4871	0.5050
	Panel B - Triadic Grants			
has_female	-0.0116***	-0.0039	-0.0040	-0.0011
	(0.0029)	(0.0000)	(0.0040)	(0.0038)
Observations	446,745	437,619	434,399	434,012
R-squared	0.0812	0.3464	0.4018	0.4144
	Panel C - Renewals (4- year)			
has_female	-0.0082***	-0.0033	-0.0017	-0.0019
	(0.0024)	(0.0028)	(0.0026)	(0.0026)
Observations	446,655	437,528	434,311	433,924
	0.0402	0.2733	0.3479	0.3492
Class-Year FE	YES	YES	YES	YES
Assignee FE	NO	YES	YES	YES
Examiner FE	NO	NO	YES	YES
Controls	NO	NO	NO	YES

Notes: We restrict the sample to patents with one inventor, and repeat the models in table 2, excluding team size which is now equal to 1.

Table 4: Patent outcome and gender composition- mixed gender teams

	Panel A: Mixed gender or all female teams		
	(1)	(2)	(3)
VARIABLES	**Forward Citations (5y)**	**Triadic Grant**	**Patent Renewal (4y)**
Mixed Gender	-1.5509***	-0.0088***	-0.0024**
	(0.3999)	(0.0017)	(0.0010)
All Female	0.0972	-0.0074*	-0.0026
	(0.5996)	(0.0042)	(0.0023)
Observations	1,553,161	1,553,032	1,552,752
R-squared	0.3536	0.3511	0.2741
	Panel B: Mixed gender with first inventor fixed effects		
VARIABLES	**Forward Citations (5y)**	**Triadic Grant**	**Patent Renewal (4y)**
Mixed gender	-1.4242***	-0.0042**	-0.0009
	(0.3822)	(0.0017)	(0.0012)
Mixed gender x	0.7575	0.0151	0.0010
Female1	(0.8560)	(0.0095)	(0.0060)
Observations	932,778	932,754	932,503
R-squared	0.6387	0.6665	0.4983

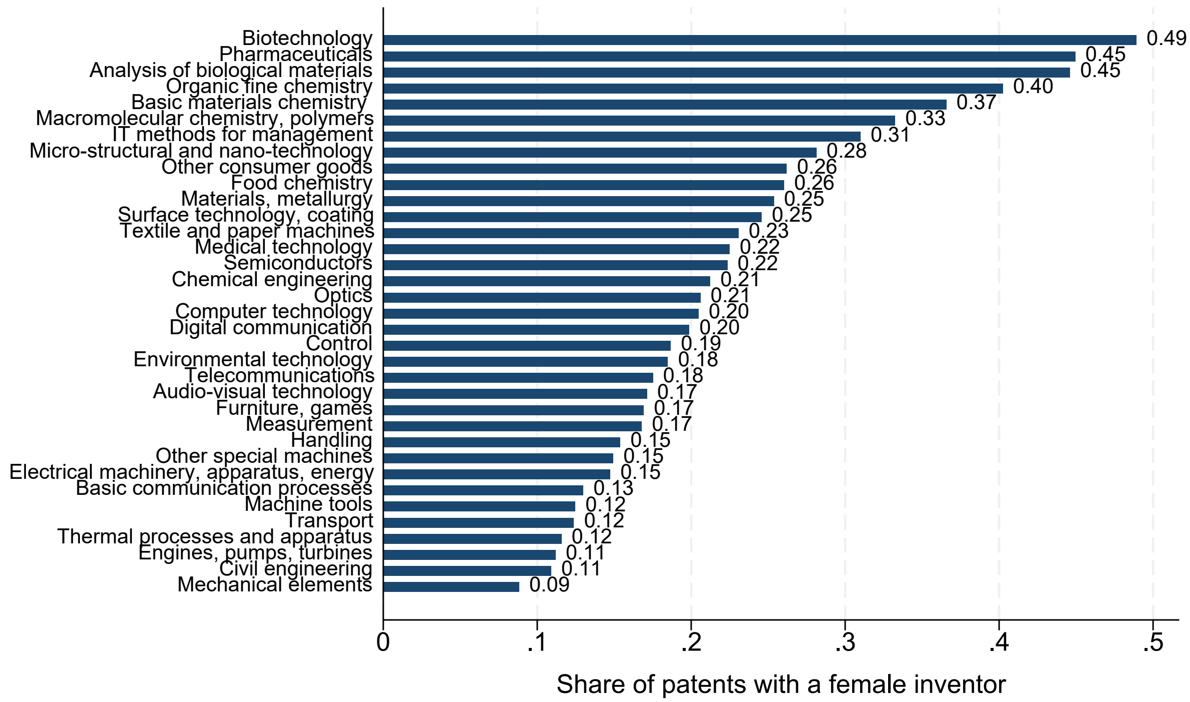
Notes: All models include class by year, assignee, art unit by examiner fixed effects, examiner experience and patent attributes. Panel B also includes first inventor fixed effects. Mixed gender is equal to 1 if the team has at least one female inventor and at least one male inventor. In panel A we include an "all-female" dummy and in panel B, we include the interaction of mixed gender with an indicator for a female first inventor. In each panel, each column shows estimates for a different outcome.

Table 5: The gap in different groups of assignees

Assignee group interacted with *has_female*	(1) Forward Citations (5y)	(2) Triadic Grant	(3) Patent Renewal (4y)	Share of patents in group	Share with a female inventor.
Education	-4.0216***	-0.0298***	-0.0056*	4%	35%
	(0.7788)	(0.0047)	(0.0031)		
Institutions and foundations	-5.1319***	-0.0222*	0.0087	1%	32%
	(1.1431)	(0.0124)	(0.0060)		
Government	-0.6535	-0.0237***	0.0385*	1%	25%
	(0.4385)	(0.0027)	(0.0230)		
Companies with					
Low # patents & low share female	-2.9472***	-0.0242***	-0.0056***	32%	5%
	(0.7107)	(0.0036)	(0.0019)		
Low # patents & high share female	-0.6198	0.0011	-0.0003	15%	39%
	(1.0180)	(0.0031)	(0.0019)		
High # patents & low share female	-1.4970*	-0.0074**	-0.0016	17%	13%
	(0.7697)	(0.0033)	(0.0020)		
High # patents & high share female	-0.7135	-0.0057**	-0.0041***	30%	25%
	(0.4946)	(0.0028)	(0.0015)		
Constant	9.3835***	0.0609***	0.9049***		
	(1.1852)	(0.0048)	(0.0084)		
Observations	1,553,096	1,552,967	1,552,687		
R-squared	0.3537	0.3512	0.2741		

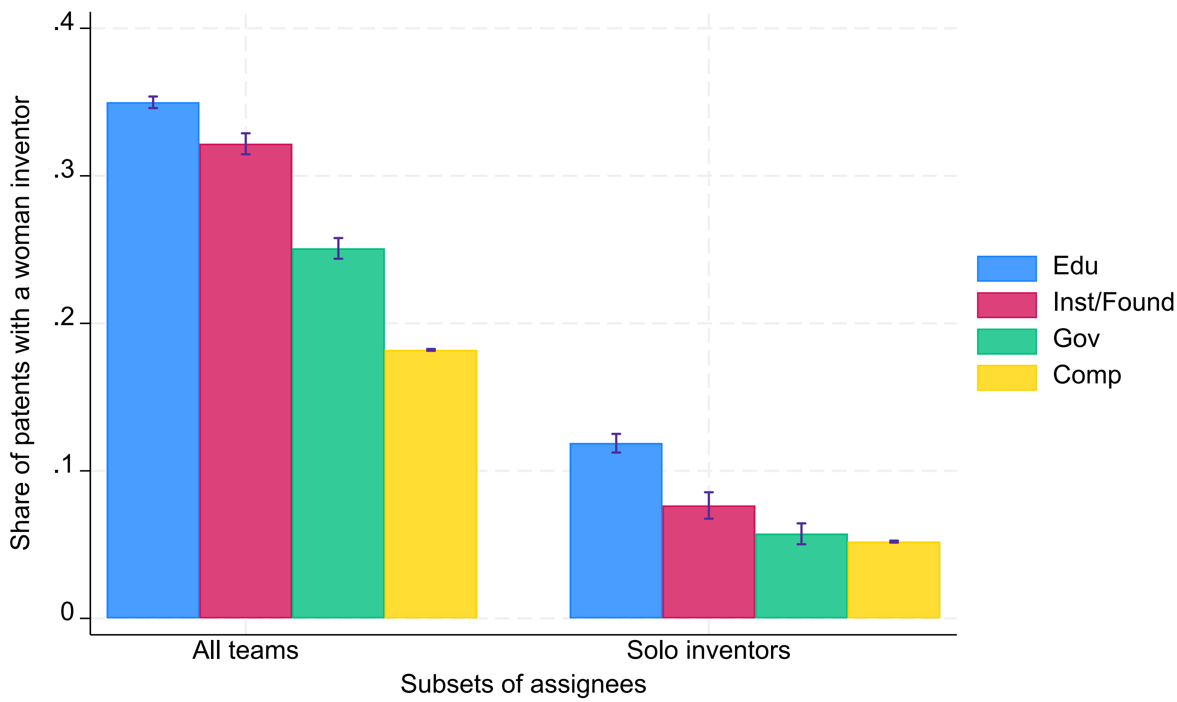
Notes: Assignees were partitions to 7 groups. All models include patent class by application year fixed effects, assignee fixed effects and art unit by examiner fixed effects, examiner experience and patent attributes. The variables of interest are interactions of group dummies and the *has_female* dummy. Standard errors are clustered at the fixed effect level. Columns 1-3 show regressions for the three outcomes, the last two columns show the share of all patents in the group, and the share of patents in each group that have a female inventor.

Figure 1 – Share of patents with at least one female inventor by technology field.



Notes: Figure uses our patent dataset and technology field classification from the OECD dataset.

Figure 2 – Share of patents with at least one female inventor in different groups of assignees



Note: We group assignees based on the assignee name. We classified as edu assignees whose name includes keywords university, college, school and institute of technology. We classified as government assignees whose name included variations of United States of America As", United States government or United states Department. We classified as institutions and foundations names including one of these words, as well as hospitals and research centers that were not in the edu category. Remaining assignees are classified as companies. The following figure illustrates variation in types of assignees where women inventors are more likely to participate in patenting.

Appendix

Robustness tests: We checked robustness of our results by considering additional outcomes (Table A1), differences in our measure of gender composition (Table A2), and a less restrictive sample, keeping patents even if some (but not all) inventor's gender are known. The following tables show these estimates.

Table A1.1: Patent outcomes (longer term) and the gender composition of teams

VARIABLES	(1) Tech-Year	(2) Assignee	(3) Examiner	(4) Controls
	Panel A - Forward Citations (7-year)			
has_female	-4.7310***	-3.1151***	-2.9559***	-1.8210***
	(0.3160)	(0.5574)	(0.5290)	(0.4666)
Observations	1,555,846	1,555,718	1,553,166	1,553,161
R-squared	0.0786	0.2999	0.3377	0.3659
	Panel B - Renewals (8- year)			
	(5) Tech-Year	(6) Assignee	(7) Examiner	(8) Controls
has_female	-0.0229***	-0.0056***	-0.0041**	-0.0048***
	(0.0015)	(0.0019)	(0.0017)	(0.0017)
Observations	1,108,450	1,103,281	1,100,614	1,099,245
R-squared	0.0404	0.2626	0.3199	0.3225
Class-Year FE	YES	YES	YES	YES
Team size	YES	YES	YES	YES
Assignee FE	NO	YES	YES	YES
Examiner FE	NO	NO	YES	YES
Controls	NO	NO	NO	YES

Notes: All models are estimated using linear high dimensional fixed effects models (Stata's reghdfe). All models include patent class by application year fixed effects and team size dummies. We gradually add assignee fixed effects in column (2), art unit by examiner fixed effects and examiner experience in column (3) and patent attributes in column (4). In each column, we cluster standard errors at the fixed effects levels.

Table A1.2: Patent outcomes (longer term) and the gender composition of solo inventors

VARIABLES	(1) Tech-Year	(2) Assignee	(3) Examiner	(4) Controls
		Panel A - Forward Citations (7-year)		
has_female	-3.2650***	-0.0538	-0.2548	0.4420
	(0.6741)	(1.1997)	(0.8332)	(0.7805)
Observations	446,398	437,263	434,046	434,044
R-squared	0.0707	0.4325	0.5030	0.5191
		Panel B - Renewals (8- year)		
	(5)	(6)	(7)	(8)
	Tech-Year	Assignee	Examiner	Controls
has_female	-0.0182***	-0.0021	-0.0003	-0.0016
	(0.0039)	(0.0046)	(0.0043)	(0.0043)
Observations	332,560	322,790	319,451	319,087
R-squared	0.0600	0.3280	0.4108	0.4130
Class-Year FE	YES	YES	YES	YES
Team size FE	YES	YES	YES	YES
Assignee FE	NO	YES	YES	YES
Examiner FE	NO	NO	YES	YES
Controls	NO	NO	NO	YES

Notes: All models are estimated using linear high dimensional fixed effects models (Stata's reghdfe). All models include patent class by application year fixed effects and team size dummies. We gradually add assignee fixed effects in column (2), art unit by examiner fixed effects and examiner experience in column (3) and patent attributes in column (4). In each column, we cluster standard errors at the fixed effects levels.

Table A2.1: Patent outcome and share of female

	(1)	(2)	(3)	(4)
VARIABLES	class-year	Assignee	Examiner	Controls
Panel A - Forward Citations (5-year)				
Female_share_team	-6.4918***	-3.8919***	-3.7272***	-1.9585***
	(0.4351)	(0.6979)	(0.6391)	(0.5719)
Observations	1,555,846	1,555,718	1,553,166	1,553,161
R-squared	0.0697	0.2844	0.3222	0.3536
Panel B - Triadic Grants				
Female_share_team	-0.0238***	-0.0239***	-0.0165***	-0.0238***
	(0.0039)	(0.0036)	(0.0033)	(0.0039)
Observations	1,557,063	1,554,502	1,553,032	1,557,063
R-squared	0.3114	0.3335	0.3511	0.3114
Panel C - Renewals (4- year)				
Female_share_team	-0.0059***	-0.0045**	-0.0046**	-0.0059***
	(0.0022)	(0.0019)	(0.0019)	(0.0022)
Observations	1,556,892	1,556,783	1,554,222	1,552,752
R-squared	0.0279	0.2221	0.2728	0.2741
Class-Year FE and team size	YES	YES	YES	YES
Assignee FE	NO	YES	YES	YES
Examiner FE	NO	NO	YES	YES
Controls	NO	NO	NO	YES

Notes: All models are estimated using linear high dimensional fixed effects models (Stata's reghdfe). All models include patent class by application year fixed effects and team size dummies. We gradually add assignee fixed effects in column (2), art unit by examiner fixed effects and examiner experience in column (3) and patent attributes in column (4). In each column, we cluster standard errors at the fixed effects levels.

Table A2.2: Patent outcome and the gender of the first inventor

	(1)	(2)	(3)	(4)
VARIABLES	class-year	Assignee	Examiner	Controls
		Panel A - Forward Citations (5-year)		
Female_first_inventor	-2.8623***	-1.6795***	-1.5888***	-0.5605
	(0.3967)	(0.4497)	(0.4319)	(0.4124)
Observations	1,555,846	1,555,718	1,553,166	1,553,161
R-squared	0.0694	0.2843	0.3221	0.3536
		Panel B - Triadic Grants		
Female_first_inventor	-0.0190***	-0.0131***	-0.0132***	-0.0088***
	(0.0017)	(0.0027)	(0.0025)	(0.0024)
Observations	1,557,161	1,557,063	1,554,502	1,553,032
R-squared	0.1002	0.3114	0.3335	0.3510
		Panel C - Renewals (4- year)		
Female_first_inventor	-0.0120***	-0.0014	-0.0012	-0.0009
	(0.0012)	(0.0014)	(0.0013)	(0.0014)
Observations	1,556,892	1,556,783	1,554,222	1,552,752
R-squared	0.0278	0.2221	0.2728	0.2741
Team size FE	YES	YES	YES	YES
Class by Year FE	YES	YES	YES	YES
Assignee FE	NO	YES	YES	YES
Examiner FE	NO	NO	YES	YES
Controls	NO	NO	NO	YES

Notes: All models are estimated using linear high dimensional fixed effects models (Stata's reghdfe). All models include patent class by application year fixed effects and team size dummies. We gradually add assignee fixed effects in column (2), art unit by examiner fixed effects and examiner experience in column (3) and patent attributes in column (4). In each column, we cluster standard errors at the fixed effects levels.

Table A3: Patent outcome and the gender composition of teams (keep missing gender)

	(1)	(2)	(3)	(4)
VARIABLES	class-year	Assignee	Examiner	Controls
		Panel A - Forward Citations (5-year)		
has_female	-3.6233***	-2.2662***	-2.1471***	-1.1572***
	(0.2408)	(0.3917)	(0.3737)	(0.3285)
Observations	1,797,242	1,797,112	1,794,640	1,794,634
R-squared	0.0679	0.2855	0.3184	0.3502
		Panel B - Triadic Grants		
has_female	-0.0174***	-0.0120***	-0.0119***	-0.0078***
	(0.0011)	(0.0018)	(0.0017)	(0.0016)
Observations	1,798,777	1,798,681	1,796,201	1,794,498
R-squared	0.1048	0.3074	0.3273	0.3453
		Panel C - Renewals (4- year)		
has_female	-0.0127***	-0.0031***	-0.0023**	-0.0022**
	(0.0009)	(0.0011)	(0.0009)	(0.0009)
Observations	1,798,449	1,798,342	1,795,862	1,794,159
R-squared	0.0276	0.2165	0.2656	0.2670
Class-Year FE and team size	YES	YES	YES	YES
Assignee FE	NO	YES	YES	YES
Examiner FE	NO	NO	YES	YES
Controls	NO	NO	NO	YES

Notes: We keep all patents with at least one observed inventor's gender, even if some are missing. All models are estimated using linear high dimensional fixed effects models (Stata's reghdfe). All models include patent class by application year fixed effects and team size dummies. We gradually add assignee fixed effects in column (2), art unit by examiner fixed effects and examiner experience in column (3) and patent attributes in column (4). Has female is equal 1 if at least one observed inventor gender is female.