Are Patent Examiners Gender Neutral?*

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Abstract

This paper studies the prevalence and evolution of gender bias in the United States Patent and Trademark Office (USPTO) examination process and assesses the consequences of this bias on economic outcomes. Applying Natural Language Processing tools to patent applications submitted between 2001 and 2013, I estimate gender gaps conditional on the content of the patent application, comparing allowance probabilities between teams of inventors with different gender compositions but similar inventions. Despite a substantial raw gender gap in the probability of initial allowance, I document no average difference in initial allowance rates between mixed-gender and all-male teams. This average masks important heterogeneity. Allowance rates for mixed-gender teams were significantly lower between 2001 and 2003, a gap that shrank to zero by 2005. Gender gaps also vary substantially across examiners, with bias against mixed-gender patents concentrated among senior examiners and bias in favor of women concentrated among young examiners. A mean zero gender gap with positive variance generates economic loss due to the misallocation of granting rights. Building on the methodology of Kogan et al. (2017), I estimate that these biases depressed the value of approved patents by $12.6 million per year.

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1 Introduction

Over 200 years have passed since Hannah Wilkinson Slater became the first woman to be granted a patent in the United States.[1] Although female participation rates in the education system and labor market have risen dramatically since then, women nonetheless remain grossly underrepresented in the patenting system, accounting for only 12% of the inventors in 2016 (Lissoni et al., 2018). While various explanations have been offered for this persistent gender gap, including differences in occupation choice (Hunt et al., 2013), rejection aversion (Subramani et al., 2021), and lack of exposure to innovation (Bell et al., 2019), the concern that gender bias causes patent examiners to over- or under-value contributions based on inventors' gender persists. Such a concern is particularly pronounced in the US patenting systems in which examiners' discretion has been documented to be consequential in allowance decisions (Frakes and Wasserman, 2017; Sampat and Williams, 2019). Bias in patenting generates not only equity but also efficiency concerns. Misallocation of patent rights could result in long-run real economic consequences as patents and innovative activities drive economic growth (Bloom et al., 2013; Akcigit et al., 2017; Acemoglu et al., 2018), and are meaningful for inventors' careers (Toivanen and Vaananen, 2012; Kline et al., 2019) and firm profits (Hall et al., 2005; Galasso and Schankerman, 2015; Kogan et al., 2017).

Previous attempts to estimate the importance of gender bias in the patent system suffer from several fundamental concerns. Jensen et al. (2018) have documented a gender gap in the likelihood a patent is granted. However, a gender gap in granting doesn't necessarily imply gender bias. The patent-granting process comprises multiple rounds of revisions before a patent is actually granted, and Subramani et al. (2021) show that women are less likely to persist and resubmit their patent applications after early rejections. Efforts to investigate gender differences in the first-round examination decisions have estimated a smaller and insignificant gender gap (Choi et al., 2019). Even so, all previous estimates comparing allowance rates by gender are susceptible to omitted variable bias, as gender gaps could result from a correlation between inventors' gender and the unobserved patent quality.

In this paper, I address this concern by exploiting state-of-the-art tools from the Natural Language Processing (NLP) literature to control for the patent application text and content.

[1]Her patent was registered in 1793 and introduced a new method of producing cotton-sewing thread. Interestingly, the inventor's name on the patent was Mrs. Samuel Slater, her husband's name (Khan, 1996; USPTO, 1888).

I analyze whether the inventors' gender, implied by their name on the patent application, affects the outcome of the application process conditional on rich measures of patent quality and content, as captured by the text of the application. I estimate the overall and examiner-level gender disparities in initial allowance decisions and study the characteristics of biased examiners between the years 2001 and 2014.

I encode the patent text by transforming it into *text-embeddings*, a moderate-size vector of text features generated by a pre-trained BERT (Devlin et al., 2018) neural network model that was trained exclusively on nearly the entire corpus of patents by Google (Srebrovic and Yonamine, 2020). I show that the patent text embeddings are highly predictive of both examiners' decisions, citations, and assignees' stock market return, suggesting the text embeddings account fo the patent quality. Moreover, to identify examiner-level gender bias, I provide evidence that the assignment of applications to examiners is as good as random conditional on the text embeddings. I show that conditional on the text embeddings, the gender mix of the inventors and other non-text characteristics are *not* systematically correlated with examiner characteristics.

The measure of bias I estimate – the gender gap in allowance conditional on the text – captures two distinct but related forms of disparities: disparate treatment and disparate impact. Disparate treatment arises when the decisions of the examiners are directly a function of the gender composition of the inventors' team, such as in models of taste-based discrimination (Becker, 1957), inaccurate stereotypes (Bordalo et al., 2016), or statistical discrimination (Aigner and Cain, 1977). Disparate impact results from behavior based on other non-text characteristics that are not the gender of the inventors but are correlated with it. This type of disparity was formalized in Bohren et al. (2022) and studied in the legal system in Arnold et al. (2022). In either case, the bias I measure is policy-relevant as USPTO examiners are legally required to rely primarily on the patent application's text and claims.

I document three novel facts about the distribution of gender bias in the first round of the patent application process. First, while the raw gender gap in initial allowance is substantial, after controlling for the text, the average gender gap entirely disappears. This result is robust to different gender definitions, including thousands of art units,[2] year, and class fixed effects, and alternative matching estimates. Second, I document the evolution of gender bias in

[2]an art unit is an examination unit, a group of examiners specializing in a particular technology

patent applications from 2001 to 2013. I find that between 2001 and 2003, patents with mixed-gender authors were 0.8 percentage points less likely to be initially allowed compared to all-male or gender-unknown patents. However, that gap has decreased over time, and since 2005, it has converged to zero. This finding mirrors the recent evidence from academia (Card et al., 2021, 2022) and labor markets (Schaerer et al., 2023) indicating that the gender bias has decreased over time and turned in favor of women in some cases. Lastly, I show that, although the mean gender bias is zero, there is substantial variation in bias across examiners. After adjusting for sampling error using the leave-out estimator of Kline et al. (2020), the standard deviation of gender bias across examiners in initial allowance is 2.3 percentage points, more than 25 percent of the mean initial allowance rate for no-female teams. Such two-sided gender discrimination has also been found in audit experiments in the labor market (Arceo-Gomez and Campos-Vazquez, 2014; Kline and Walters, 2020; Kline et al., 2022).

Examiner discretion plays a significant role in allowance decisions even beyond the gender of the inventors. After controlling for the patent text embeddings, I document substantial variation in examiner leniency, with a standard deviation of 110% of the average initial allowance rates. While previous literature has emphasized the importance of discretion in the examination process (Lemley and Sampat, 2012; Frakes and Wasserman, 2017; Sampat and Williams, 2019; Farre-Mensa et al., 2020), to my knowledge, this is the first estimate of examiners' leniency that accounts for sampling error and conditions on the content of the patent.

Next, I study whether some groups of examiners are more discriminatory than others. I find that examiner seniority and patent art unit partially explain the variation in gender bias across examiners. Examiners' start year at the USPTO explains roughly 25% of the variation in gender bias, with senior examiners more likely to exhibit bias toward mixed-gender patents and younger examiners more likely to be biased against all-male patents. Time effects do not explain this result, ruling out the possibility that examiners changed their behavior over time. The art unit of examiners explains approximately 25% of the variation in gender bias, suggesting a wide across-field variation.

Next, I study the variability of gender bias within examiner characteristics and over time. I find that the standard deviation of the gender bias of male examiners is twice the size of the standard deviation of female examiners, suggesting that male examiners pose a higher risk in the system. Similarly, I find that younger cohorts of examiners who joined the USPTO in later years have lower levels of variability in discretion and bias. Finally, combining these findings with the evidence that the mean preferences of younger examiners differ from those of senior examiners, I conclude that, over time, the risk of encountering an abnormally biased examiner has increased. This result suggests an increase in polarization within the community of examiners.

Exploring the legal ground behind initial rejections reveals that although most rejections are based on a lack of novelty or obviousness, the gender gaps in initial allowance are disproportionally correlated with technical rejections based on writing. Previous research argues that such rejections are simpler and less time-consuming as they do not require a timely prior-art search (Frakes and Wasserman, 2017).

Much of the discrimination literature focuses primarily on average gaps, which only partially map to fairness and inefficiencies. First, even though there is no ex-ante bias on average, heterogeneity in bias undermines ex-post horizontal equity. Second, an exclusive focus on mean bias overlooks the detrimental ramifications of misallocation, which may manifest even if the mean bias is zero. Utilizing Kogan et al. (2017)'s stock market return model for patents, I estimate the effect of bias on the stock market returns of publicly traded firms. Since the stock market return is observed only for granted patents, I estimate a selection model (Heckman, 1979), exploiting the examiners as instruments, conditional on the patent content. My analysis estimates the annual cost of having a positive variance in gender bias among initially allowed patent applications assigned to publicly traded firms to be approximately \$1.67 million. Extrapolating this cost to granted applications, the results suggest that gender bias generates a loss of 12.6 million Dollars per year. Finally, extending this cost to any form of examiner-level discretion reveals a cost of 76.6 million Dollars per year, which is 31% of the value of the median public US firm in 2013.

This paper contributes to several strands of the literature. First, this paper is the first systematic evaluation of gender bias in the USPTO patent application process that accommodates major identification concerns. Closely related work by Coluccia et al. (2023) provides evidence for racial discrimination in patenting during the 20th century in the US, and Li and Liu (2023) estimates gender gaps in citations. More broadly, this paper contributes to the literature on the lack of recognition and under-representation of female scientists (Rossiter, 1993; Silver et al., 2018; Ellinas et al., 2019; Koffi, 2021; Sarsons et al., 2021), and aligns with literature in economics studying discrimination and how it varies across gate-keepers (Abrams et al., 2012; Arnold et al., 2018, 2020; Feigenberg and Miller, 2022; Kline et al., 2022). Beyond documenting gender bias, this paper is among the studies that evaluate the economic effects of discrimination (Becker, 1957; Glover et al., 2017), and the consequences of inefficiencies in the innovation process (Bryan and Williams, 2021; Clemens and Rogers, 2023; Matcham and Schankerman, 2023).

Methodologically, this paper exploits recent advancements in the NLP literature and builds a matching estimator that conditions on the patent application text (for a review on the use of text in economics, see Gentzkow et al., 2019).[3] This paper is among the first to provide a concrete and easy-to-implement method to account for the patent application text exploiting modern NLP methods. Using moderate dimensional embeddings, I demonstrate that these embeddings can balance observables of patent applications across inventing teams with different gender mixes, suggesting that these comparisons are unconfounded. The approach taken in this paper could serve as a useful framework to study questions in other settings where evaluations are mandated to depend on textual content.

The rest of the paper is organized as follows. Section 2 provides the institutional background, and Section 3 describes how I use the text data for analysis, Section 4 describes the patent data and the text embedding features, and Section 5 outlines the conceptual framework and identification assumptions for the overall gender bias estimate. Section 6 reports the average gender bias overall and by years and examiners' years of experience. Section 7 discussed the identification assumptions for the examiner-level gender bias. Section 8 documents the variance components of gender bias and its variation across groups. Section 9 provides robustness tests and mechanisms. Section 10 estimates the impacts of bias on market return, and Section 11 concludes.

[3]Examples for matching on text in social science include: Roberts et al. (2020) who model the text with latent Dirichlet allocation (LDA) model, Mozer et al. (2020) who match the text using distance metrics on the bag-of-words representation, and Zeng et al. (2022) which use bag-of-words methods to extract covariates from medical records to study the effect of different treatments on cancer. Keith et al. (2020) provides a review of using textual data to adjust for confounding from the computer science perspective.

2 Institutional Background

2.1 Patent Examination Process

A patent application is a form describing an invention that is being requested for a grant at the patent office. It includes a title, written description, abstract, at least one claim, and, if necessary, some drawings and is usually written by patent attorneys using legal language. Once the USPTO receives the application, it undergoes a pre-examination review to ensure that all necessary forms have been completed and all fees have been paid. The application claims are then classified and forwarded to the relevant USPTO technology center and art unit[4] for examination.

Within an art unit, a supervisory examiner (SPE) assigns the application to a specific examiner, who oversees the application for the remainder of its existence. Previous research argues that, at least in some art units, applications are assigned to examiners randomly (Frakes and Wasserman, 2017; Sampat and Williams, 2019). However, other evidence also indicates within art unit specialization by class and subclass (Righi and Simcoe, 2019). Irrespective of whether the assignment is random within art units, all existing evidence suggests that it is the content of the application that plays a central role in how applications are assigned to examiners.

The assigned examiner then evaluates the application content for compliance with law and regulation. She makes sure that the patent claims include only a single invention,[5] that the claims clearly define the invention, and that the description describes the invention adequately. The examiner also conducts a prior art search by looking for related previous patents or non-patent literature to determine whether the claimed invention is novel and not obvious. Based on this examination, the examiner may either allow all claims, an event I refer to as Initial Allowance (IA), or issue an office action indicating a Non-Final Rejection rejecting or objecting to one or more of the claims made in the application. A typical non-final rejection office action identifies the specific claims and the grounds on which each of them is being objected to and/or rejected.

[4]Technology Centers are groups of examination units divided by a broad technology. Each examination unit is called an art unit.

[5]If multiple inventions appear in the claims, the examiner issues a restriction, and the applicant is then required to choose claims drawn to a single invention.

Upon receiving a Non-Final Rejection, the applicant is generally given three months to respond. The applicant's response is some combination of arguments and amendments to the claims, usually narrowing their scope. The applicant may also ask for a telephone or in-person interview with the examiner.[6]

2.2 The Role of the Patent Application Text

The patent application text has a central and significant role in the application process. Based on the text, patents are classified into classes and subject matter, which determine the specific technology centers, art units, and examiners to which they are assigned. Upon assignment, the Patent Act defines the criteria for examiners when assessing the patentability of an invention to be based primarily on the information in the patent applications.

An examiner can deny an invention for several reasons. One is lack of novelty and obviousness, which requires the examiner to compare the claimed invention with prior art. Other grounds for denial are missing statutory subject matter, non-usefulness of the proposed invention, inadequate writing, and failure of the application to satisfy disclosure requirements, all assessed based on the patent text and its content. All other non-patent-text information, such as existing prior art, citations from the non-patent literature, and personal knowledge, are allowed to be used only in conjunction with the patent text.

While each patent application is required to identify the inventors in the applications properly, the inventors' names are not expected to be used for assessing patentability. At the least, names cannot serve as reasonable grounds for rejection. Moreover, the role of uncertainty is also limited in the patent application process. Unlike in academic papers, whose content could change dramatically during the review process, the invention and its technology are not allowed to be changed after a patent application has been submitted. Instead, a patent application should represent a final output. Should inventors seek to change their invention, they must file a new application with a new set of claims. Amendments are allowed only within the scope of the claims. Examiners, of course, can still face uncertainty or have varying skills in identifying high-quality patents. In my analysis, any systematic

[6] An interview with the applicant or the applicant's attorney for the discussion of the patentability of a pending application will not occur before the first Office action unless the application is a continuing or substitute application. This paper excludes continuation applications and analyzes decisions only at the first stage of the application process.

variation linked to the inventor's gender, resulting from such discrepancies, is considered evidence of bias, as I formally outline in Section 5.

The unique setting of the patent examination process and the important role played by the patent application text lead to the following question: can we match patent applications based on their text? In the following sections, I provide a framework to do so and further evidence for its validity.

3 Text as Data

"You shall know a word by the company it keeps!"

- John Firth, "A synopsis of linguistic theory, 1930-1955", 1962.

Text is a form of unstructured, high-dimensional data that encodes rich information. This property has led generations of scientists and linguists to develop methods for numerical text representation. In this paper, I follow the state-of-the-art NLP solution of text representation and assume that words can be represented as *word embeddings*, dense real-valued vectors of a finite dimension dwelling in some predefined vector space. Each vector dimension is associated with a feature that represents different aspects of the word, and each word is represented by a point in the vector space such that words with the same meaning are closer to each other.

This approach to text representation is based on the *Distributional Hypothesis* from the literature on distributional semantics in linguistics, an idea first popularized by Firth (1957). It is derived from the semantic theory of language usage, in which lexical items (words, sentences, or paragraphs) that are used and that occur in similar contexts tend to convey similar meanings. This representation, which has led to unprecedented success in multiple Artificial intelligence (AI) tasks, is thus considered one of the key breakthroughs in NLP research in recent years.

In this section, I describe in detail how I use the neural network language model BERT (Devlin et al., 2018) to convert the high-dimensional patent application text inputs into text embeddings, thereby creating a list of p continuous covariates $x_{i1}, ..., x_{ip}$, where p is of moderate size.

3.1 Contextualized Word Embeddings Using BERT Model

The Bidirectional Encoder Representations from Transformers, known as the BERT model (Devlin et al., 2018), is a deep neural network model trained simultaneously to predict two unsupervised tasks. The first task is to randomly predict a certain percentage of the words in each paragraph, and, given a pair of sentences, the second task is to predict whether one sentence proceeds another. In this section, I briefly describe the BERT model's main structure and how it generates word embeddings. See the original paper (Devlin et al., 2018) for more detailed information.

The BERT model is a neural network model, a statistical model inspired by neuroscience, which allows for high levels of dependencies and nonlinearities between inputs. Illustrated in appendix Figure A.1, any neural network model can be represented as a graph comprising input, hidden, and output layers. Each node in the graph is called a neuron, and each edge represents an estimated parameter such that each neuron is a function of the linear combination of the neurons from the previous layer. In the BERT model, the input layer is a piece of text, represented by a dummy for each word, and each word dummy is then mapped to several hidden layers of a moderate dimension. Between layers, different words are connected using a special attention layer architecture (Vaswani et al., 2017). Each model's hidden layer is considered to be an embedding vector, representing a word in a lower dimensional space.

To prepare the input of the BERT model, each word in the input text is broken into subwords and tokenized, and a special token, termed the [CLS] token, is added to the beginning of the text. Then, in the last layer, the model predicts the two tasks described above: predicting the masked word using its embedding representation and predicting the next sentence using the last layer embedding of the special [CLS] token.

The outputs of a pretrained model are the estimated parameters of each neural network layer. As such, there are several possible options to generate word embeddings. Devlin et al. (2018) suggest using BERT embeddings in various ways, including the last, second-to-last, or concatenating the last four layers. Moreover, to represent a document comprised of many paragraphs, it is customized to use either the average word embeddings in the paragraph or the embeddings of the first special [CLS] token as an aggregate representation of the entire paragraph. In this work, I use the [CLS] token as a text representation. In Section 4.2, I compare different combinations of embedding layers and proceed with those that attain the highest predictive power subject to my machine memory constraint.

To generate the word embeddings, I utilize a pretrained large BERT model that was trained exclusively on over 100 million patents by Google (Srebrovic and Yonamine, 2020) and on all the parts of the text, including the abstract, description, and claims. The model has 24 hidden layers, each embedding vector is of a size of 1024, and each input text could have up to 512 tokens. Since the language model was estimated exclusively on patents, the estimated parameters represent the language structure, word distribution, and unique semantics of the specific domain of patents.

The BERT word embeddings, among other deep neural network NLP models, are known for their high predictive power. AI and data science applications have long used the word embeddings generated using BERT or similar models. In Section 4.2, I show that also in this setting, the patent application text embeddings have high predictive power for the content of patents, allowance probability, and the decisions of the examiners and that they can be used as covariates in causal questions.

4 Data

The primary data source employed in this research is the USPTO Patent Examination Research Dataset (Graham et al., 2015) which includes the universe of all public patent applications available online in the Public Patent Application Information Retrieval system (Public PAIR) (Miller, 2020). I restrict the sample to utility[7] patent applications filed after November 29th, 2000[8] and before January 1st, 2014. For every patent application, the Public PAIR data includes information on inventors' first and last names and additional variables such as country, application number, publication number, the grant date if granted, and examiners, art unit, and technological classes and sub-classes identifiers. To avoid detecting differential behavior to non-US inventors, I include only patent applications submitted by US inventors.

I merge this dataset with several other datasets: 1) The USPTO Patents View data, which includes detailed information on both granted patents and patent applications. 2) The Patent

[7]Utility patents are granted for the "invention of a new and useful process, machine, manufacture, or composition of matter" (USPTO 2010).

[8]Since the American Inventors Protection Act of 1999, almost all the USPTO patent applications filed after November 29th, 2000 were published online, regardless of whether they are granted or not.

Claims Research Dataset (Marco et al., 2019) from which I obtain detailed information on the number of claims per patent, claim text, and the change in the claims between application to granting for granted patents; 3) "Google Patents Research Data" from which I pull the abstract and description text of each patent application; 4) Examiners' roster, pay scale, and education levels from Frakes and Wasserman (2017) Freedom of Information Act request; 5) Kogan et al. (2017) patent market value data, which run event studies to estimate the excess stock market return realized on the grant date of patents assigned to publicly traded firms; 6) USPTO Office Action Rejection, which documents the grounds of rejections for all rejected patent applications from 2008 to 2017. For additional information about the patent data, see Appendix Section B.

Applicants and examiner characteristics: I assume that examiners infer the gender of inventors based on their names. To classify inventors' gender, my procedure relies on the assumption that examiners located in the US are likely to recognize the gender of names common in the US. Hence, my gender coding procedure assigns gender based on the distribution of the first name by gender provided by the US Security Administration (SSA). Using this method, I can assign gender to 75% of the names in my final sample. Names unavailable in the SSA tables are considered foreign names with unknown gender.

To code the gender of examiners, I take an improved approach, as my ultimate goal is to infer their gender as accurately as possible. Therefore, I use a collection of sources to identify the gender of the maximum amount of names, including foreign-sounding names. Specifically, in addition to the US SSA administrative tables, I use the name gender published by the United Kingdom Intellectual Property Organization, the name gender dataset published by the World Intellectual Property Organization (WIPO), the gender-guesser Python package, and the Genderize.io program. Using all these sources, I successfully identified 85% of the examiners' names.

I measure each examiner's years of experience and education level based on the FOIA roster tables provided by Frakes and Wasserman (2017), which date back to 1992 and end in 2012. To account for the accurate years of experience of examiners who joined the USPTO before 1992 or after 2012, I combine the information of the first office action and validate my approach using the administrative records. See Appendix Section B for more details.

4.1 Descriptive Statistics

Table 1 provides summary statistics of the sample of patent applications satisfying the sample restriction described above. The baseline sample includes over 1.2 million patent applications; only 16% of them include at least one female inventor, and only 11% have a female inventor as the first or second author in the inventors' list.[9] The average inventor team has 2.5 inventors, whereas teams with at least one female inventor are larger. 35% of the patent applications are of sole inventors, most of whom are male.

An initial allowance is a rare event: only 8.3% of the patent applications are allowed in the first round of examination, while 64.6% of the patent applications are eventually granted. Additionally, the raw gender gap in initial allowance and granting is substantial, as seen in the last two rows of Table 1. Patent applications with at least one female inventor are almost two percentage points less likely to find their patent initially allowed (23% compared to all male or unknown patent applications) and 6.1 percentage points less likely to eventually have their patents granted (10% compared to all male of unknown grant rate).

Table 2 reports the main descriptive statistics of the patent examiners in my analysis. There are 8,550 examiners in the sample; 2,055 were classified as female, 5,128 as male, and for 1,367, I could not classify their gender based on their name. The mean examiner-level initial allowance rate is 6.7 percentage points, with male examiners having a 1.9 higher allowance probability. In addition, 20 percent of the examiners in my sample joined the USPTO before 1995, 31 percent joined between 1996 and 2001, and the rest joined after 2001.

4.2 Selection and Visualization of the Patent Text Embeddings

The BERT model has several layers, each potentially serving as text embeddings. To choose the list of embeddings, I adhere to the following protocol: For every part of the patent application text, i.e., description and claims, I generate a unique embedding vector using the CLS token. Since the BERT text input is constrained to at most 512 tokens, I parse each piece of text into paragraphs and generate the CLS embeddings of each paragraph. The final embedding representation of each part of the text is the average BERT embedding across all

[9]The inventor's rank in the list of inventors doesn't necessarily indicate the contribution to the invention. Nevertheless, I use this measure to account for the visibility of females in the inventors' team.

the paragraphs. Then, following the recommendations in Devlin et al. (2018), I generate the embeddings vector for every part of the text using the last, second-to-last, and third-to-last layers. This procedure yields (3×2) six possible embedding vectors, each with a total of 1,023 features.[10]

The preferred set of embeddings is selected to achieve the largest improvement in adjusted R^2 when predicting Initial Allowance (IA) and any female (F) in linear regression, subject to my machine memory constraint.[11] Results of the adjusted R^2 are presented in Figure 1,[12] where darker circles indicate that more embedding vectors were included. To compare with previous literature, the "X" point displays the adjusted R^2 values obtained by regressing IA and any female on the set of art-unit-year and class fixed-effects, which are typically used to control for confounding (e.g., Jensen et al., 2018; Choi et al., 2019).

Figure 1 shows that all the possible combinations of embedding vectors dominate the art-unit-year and class fixed effects in their predictive power of mixed-gender teams. In addition, the set of embedding vectors that include at least two vectors is more likely to dominate the fixed effects in predicting IA. This result is striking since the fixed-effects control for more than 8,000 covariates, while the sets of two embeddings vectors comprised only 2,046. Additionally, it seems that the improvement in the predictive power is marginal beyond the combination of two embeddings, one from each part of the text, description, and claims. Therefore, as my preferred set of embeddings, I use the second layer of the claims and the description text. To further explore the superiority of embeddings on the art-unit-year fixed effect, Figure 2 presents the partial adjusted R^2 within art-unit-year and class fixed effects and examiner fixed effect.[13] This figure emphasizes that the embedding vector introduces new information beyond the fine text classification to classes and sub-classes.

[10] Each original embedding vector has 1024 features mapped into a probability space and, therefore, sum to one. Hence, one of the features is excluded to avoid multicollinearity.

[11] The analysis in this paper runs on a high-performance computing cluster with 768 GB of memory.

[12] For a detailed description of the adjusted R^2 values of each combination of embeddings vector see appendix Table A.1

[13] Partial R^2 measures the proportion of variation explained by the embeddings in a model with both fixed effects and embeddings that cannot be explained by the fixed effects alone. It is measured as $R^2_{partial} = \frac{SSE(FE)-SSE(X_i,FE)}{SSE(FE)} \times \frac{N-K_{FE}}{N-K_{FE}-K_{X_i}}$ where $SSE(X)$ is the sum of squared errors for a model that controls for X.

Describing embeddings: I perform two exercises to describe the embeddings vector. In the first exercise, I use the Uniform Manifold Approximation and Projection (UMAP) algorithm (McInnes et al., 2018) to reduce the dimensionality of the embedding vector and plot it in Figure 3. This figure displays this 2-dimension UMAP reduction on a random sample of 50% of the patent applications, with the differing colors representing different technology centers.

This figure communicates two pieces of information. First, although the embeddings were not directly trained to predict theology centers and fields, they are nonetheless able to predict these dimensions. Second, as a continuous index, the embeddings provide richer information than the field indicators. For example, patents from mechanical engineering technology centers that are similar to those from the computer and communication technology centers are represented as points that are closer to each other on the graph. In contrast, mechanical engineering patents that are more similar to patents from the chemical engineering technology center would appear as points on the other side of the mechanical engineering clutter. Such similarities provide a fine measure of content that imitate the way we grasp ideas as a continuous domain.

In the second exercise, I depict the distribution of the explanatory power of text embeddings in predicting initial allowance across gender groups by running the following regression:

$$IA_i = \alpha + \beta F_i + X_i' \gamma + \epsilon_i,$$

where IA_i is an indicator that equals one if patent application i was allowed at the first round of the examination process, F_i is an indicator for the presence of at least one woman in the team of inventors, and X_i is the embedding vector. One can think of the embeddings index, $X_i' \hat{\gamma}$, as measuring the patent application quality.

The distribution of the embedding index for mixed-gender applications, as shown in Figure 4, is skewed left, possibly suggesting that the proportion of low-quality mixed-gender patents exceeds that of all-male patents. However, Figure 5, which displays the embedding index distribution across technology centers, reveals significant heterogeneity. For instance, in the biotechnology center, which has the highest proportion of mixed-gender applications, the distributions for mixed-gender and all-male embedding indices are identical. This pattern could be attributed to a Roy-type model where women choose technologies based on comparative advantage or to a model with spillovers where women's productivity improves with an increased share of women.

This pattern could alternatively be explained by bias related to the patent's content, which arises when examiners undervalue feminine topics. As I elaborate in Section 5, In this paper, I focus on analyzing bias conditional on the patent application content. Studying biases in writing styles and topics would make an interesting avenue for future research beyond the scope of this paper.

5 Conceptual Framework - Overall Gender Gaps

Each patent application i is characterized by its text T_i and by F_i, the gender composition of its inventor team. For ease of notation, I refer to F_i as an indicator that equals one when the team of inventors includes at least one female. In my analysis, I also explore other fractional versions of F_i, which have no meaningful effect on the definitions described below. Since after a non-final rejection, the gender of the inventors can affect the decision of the inventors whether to persist and resubmit the patent application (Subramani et al., 2020), I restrict attention to the examination decision after the first round of the patent application process, denoted by IA_i.

Each patent application is assigned to one of $\mathcal{J}$ examiners. Let the function $J : \{1, \dots, n\} \to \{1, \dots, \mathcal{J}\}$ indicates the examiner to which application i was assigned, and define $Z_{ij} = \mathbb{1}\{J(i) = j\}$. The goal of each examiner in the examination process is to decide the patentability of each application by evaluating the patent's text and assessing its quality.

The content of each patent application text is represented by a numerical vector of a finite dimension $C_i \equiv C(T_i) \in \mathbb{R}^p$. It describes the information encoded in the text that is relevant for examination decisions, where its vector representation allows it to vary on multiple, possibly large, number of dimensions.[14] As I describe in further detail below, my empirical analysis will assume that the patent content C_i is captured by the embedding representation generated by a BERT language model.

Following the instructions in the Patent Act, allowance decisions should be based on the patent content C_i. In practice, allowance decisions might also be based on other non-text characteristics, including the patent gender F_i. Thus, I model the decision rule of each

[14]The existence of this representation is implied by the literature on distributional semantics described in Section 3.

examiner j as a function $IA_j(c, f, u)$ of the patent content $C_i = c$, the gender of the inventors $F_i = f$, and all the other non-content non-gender characteristics that affect the final decision, $U_{ij} = u$. This representation nests the model in which examiners extract the content of the patent, C_i, from the text, T_i, imperfectly and might vary by their skill to do so, all of which is captured by the U_i term.[15]

With the initial allowance decision rule, the potential first-round examination outcome of patent application i from assignment to examiner j is $IA_{ij} \equiv IA_j(C_i, F_i, U_{ij})$. Consequently, the following function describes the system-wide initial allowance decision rule at the *overall* USPTO level:

$$\tilde{IA}(C_i, F_i, \tilde{U}_i) \equiv \tilde{IA}(C_i, F_i, \underbrace{U_{iJ(i)}, Z_{iJ(i)}}_{\tilde{U}_i}) = \sum_i Z_{iJ(i)} IA_{J(i)}(C_i, F_i, U_{iJ(i)}),$$

where $\tilde{U}_i$ encompasses both examiner level non-content related tastes and shocks and the consequences of the assignment process on eventual allowance decision. Therefore, the observed initial allowance indicator of application i is $IA_i = \tilde{IA}(C_i, F_i, \tilde{U}_i)$.

The first parameter of interest is the content-adjusted overall gender gaps, which I define as:

$$\beta = \int \omega(c)(\mathbb{E}[IA_i|F_i = 0, C_i = c] - \mathbb{E}[IA_i|F_i = 1, C_i = c])dG(c), \tag{1}$$

where integrals are taken over the distribution of the patent application content $G(c)$ in the overall population. The function $\omega(c)$ gives the weights defining the estimand of interest. For example, if $\omega(c) = 1$, then β is the Average Treatment Effect (ATE). If $\mathbb{E}[IA_i|F_i = 0, C_i = c] - \mathbb{E}[IA_i|F_i = 1, C_i = c]$ does not vary with the patent content $C_i = c$, then β is the same regardless of the chosen weights. The parameter β portrays the average USPTO-wide gender gap conditional on the patent application content.

Throughout the analysis, I refer to the content-adjusted gender gap, β, as gender bias. This measure is motivated by the legal requirement that patentability decisions should be based primarily on the content and meaning of the patent invention. Therefore, any systematic variation in allowance among patents with identical content but different genders

[15] For example, rational examiners who infer the content of the patent from the text, a noisy signal, learn only a fraction $\lambda \in [0, 1]$ of the content: $\tilde{C}(T_i) = \lambda C(T_i)$ where λ is the signal to noise ration. In that case the error, $C(T_i) - \tilde{C}(T_i)$ will be represented in the error term, U_{ij}.

of inventors represents deviations from the stated mandate of the Patent Act. Such deviations could originate from various sources, which I discuss below.

5.1 Sources of Gender Gaps in Initial Allowance

To rationalize the behavior of each examiner, suppose that each patent application possesses a unique latent quality, denoted by $q_i \in \mathcal{Q} \subseteq \mathbb{R}$. The utility of each examiner, $v(d, q, f, \epsilon)$, depends on her allowance decision $d \in \{0, 1\}$, the patent quality q, and potentially the gender indicator $f \in \{0, 1\}$, and other features ϵ of either the patent, or the examiner, or both. As elaborated next, these other factors represent other potential biases of examiners, such as ones based on the race or ethnic makeup of the inventor team (Coluccia et al., 2023), together with examiner characteristics and limitations, such as time constraints (Frakes and Wasserman, 2017), and unexpected shocks.

Given the hidden nature of the quality of the patent application, the examiner forms beliefs about the distribution of quality based on the observed signals. These signals include the patent application text, from which examiners extract its content, C_i, and additional non-text characteristics, including the gender of the inventors $F_i = f$, and other factors, $U_{ij} = u$, that influence the allowance decision.[16]

Conditional on these signals, examiners hold beliefs about the distribution of quality, represented by $\tilde{\mathcal{F}}_{f,u}(q)$. Assuming rational behavior, each examiner forms decisions based on the respective posterior distribution $\tilde{\mathcal{F}}_{f,u}(q|c)$ of the quality of the patent after observing the application content c, alongside the other characteristics f and u. The initial allowance decision is chosen to maximize the examiner's expected utility, integrated over this posterior distribution:

$$IA(c, f, u) = \arg\max_{d \in \{0,1\}} \int_q v(d, q, f, \epsilon)\, \partial \tilde{\mathcal{F}}_{f,u}(q|c).$$

Note that the beliefs of the examiner about the distribution of quality may diverge from the actual distribution of quality $\mathcal{F}_{f,u}(q)$.

[16] Both U and ϵ are observed by the examiner during the evaluation of the patens. ϵ represents all the non-patent-quality characteristics that affect examiners' decisions beyond the gender mix of the inventors, and U represents all the non-patent-text characteristics that affect examiners' decisions beyond the gender of the inventors. Both include, for example, race discrimination, institutional constraints, or temporal shocks. However, tastes related to the patent text, topics, and styles would not be considered in U, although they are part of what ϵ captures.

Disparate treatment: A decision rule that directly hinges on the gender of an inventor, be it due to preferences or beliefs, constitutes a form of disparate treatment. Such a decision rule implies that there exists $c \in \mathbb{R}^p$, and $u \in \mathbb{R}^l$, for which $IA(c, 1, u) \neq IA(c, 0, u)$. The canonical disparate treatment model is Becker (1957)'s taste-based discrimination. In this model, the utility function of examiners $v(d, q, f, u)$ varies directly with the gender of the inventors. Another form of bias is statistical discrimination, emerging when the beliefs of the examiner are shaped by the actual distribution of quality $\mathcal{F}_{f,u}(q)$, and when this distribution varies with the gender of the inventors (Aigner and Cain, 1977). Finally, bias may also stem from inaccurate beliefs regarding the prior distribution of quality that vary systematically with the gender of the inventor team $\tilde{\mathcal{F}}_{f,u}(q) \neq \mathcal{F}_{f,u}(q)$ (Bordalo et al., 2016).

Disparate impact: Gender gaps could arise additionally due to a relationship between the other factors (U_{ij}) affecting the decision of examiners and the gender of the inventors. For example, if examiners directly discriminate based on ethnicity, and ethnicity is associated with the gender mix of the inventors, this would result in a non-zero value of β.[17] Gender gaps at the system-wide USPTO level could also arise from a systematic assignment of patents of a certain gender to less lenient examiners (correlation with Z_{ij}).

In Section 7, I argue that, conditional on the patent application content, the assignment process does not drive gender gaps. Although I provide evidence in Section 9.2 that the results are robust to controlling a few other non-textual characteristics like ethnicity and country of origin, it is important to note that, at the examiner level, it is not feasible to distinctly separate the gaps stemming from disparate impact and disparate treatment since the gender of inventors is not randomly assigned. Nevertheless, non-zero estimates of gender gaps are consistent with a behavior that violates the stated examination rules and results in gender disparities.

An additional instance of disparate impact that could arise in my setting is disparities due to differential tastes of writing styles of examiners, as explored in Levitskaya et al. (2022). Since the mapping from text to content is not one-to-one, as identical inventions could be described using a different combination of words, disparities might thus stem from differences in the preferences for these writing styles. Assessing the degree to which BERT

[17] Disparate impacts have been recently studied in the context of the US judicial system by Arnold et al. (2022) and conceptualized in Bohren et al. (2022).

text embeddings account for such factors presents is an interesting avenue for future research.

5.2 Identification

The definition of gender bias in this paper is motivated by the legal requirements of patent law, which mandate that allowance decisions should primarily be based on the content of the patent application text. Since we cannot directly control for the patent text, I measure differences in allowance probability conditional on the BERT text embedding vector, denoted by $X_i \equiv X_i(T) \in \mathbb{R}^k$. This section presents the assumption on the nature of the BERT embeddings vector that is required for the identification of β.[18]

Assumption A1. (BERT embeddings). The BERT embedding vector, X_i, is sufficient for the patent content C_i.

$$E[Y_i|C_i, X_i] = E[Y_i|X_i]$$

for any $Y_i \in \{IA_i, F_i\}$

Assumption A1 requires the BERT embeddings X_i to sufficiently cover all the information in C_i. While C_i can be thought of as the minimal text representation that encompasses the patent content and that is essential for the decisions examiners make, this assumption requires that the least, the BERT embeddings representation is a finer representation of the text than the content C_i. This is analogous to controlling for a fully saturated set of controls in an experiment rather than the coarsest balancing score, the propensity score. Notably, this assumption does not require that the BERT embeddings capture all the possible information in the text. It requires it only to represent all the essential elements in the examination process, such as what it claims, how it functions, and what is new about it. Moreover, since examiners are expected to determine whether the description and the claims are written clearly, the embedding vector should also capture the language and writing clarity.

While I cannot test this assumption directly, I provide evidence that the patent embeddings are strongly predictive of examiners' decisions, patent quality proxies, and inventors' gender.

[18] Throughout the analysis, I assume that the BERT embeddings are fixed and measured with no error. The extent to which measurement error in the representation of unstructured data biases the results is an area of active research in its infancy (Sellam et al., 2021; Battaglia et al., 2024). Future drafts will provide a robustness analysis to the BERT training process.

I show that the BERT embedding is more predictive of allowance decisions than 8,000 art units by year and class fixed effects. Moreover, the BERT embedding vector is shown to be strongly predictive of both rejection reasons and patent technology classes.

Under Assumption A1, the overall gender bias (1) is non-parametrically identified. To estimate this parameter from finite data, additional parametric assumptions are required. In the analysis that follows, my preferred estimate is the Ordinary Least Square (OLS) coefficient of a female indicator, controlling linearly for the text representation. I show in Section 5.3 that the results are robust to other matching techniques.

5.3 Justifying Identification Assumptions

5.3.1 BERT Embeddings are Predictive of Patent Quality

To assess whether the embedding vector effectively represents the content and quality of the text, Appendix Figure A.2 displays a split sample binned scatter plot of the OLS predictions of allowance decisions and the patent quality proxies. In subfigures (a)-(d), I plot the forecasts of all the rejection reasons defined by the patent law: rejections based on obviousness, rejections based on novelty, rejections based on writing, and rejections based on violating eligibility criteria. The first two require understanding the invention, its uniqueness, and its contribution, while the last two are more technical and require following several guidelines the law defines. The plots reveal that even the simplest linear model strongly predicts examination decisions.

The BERT embeddings are also predictive of proxies of patent quality. Subfigures (e) and (f) repeat the same exercise and predict two well-documented quality proxy variables: log number of citations and log Kogan et al. (2017)'s market return. Similarly, the BERT embeddings are found to be strongly predictive of these variables. Surprisingly, the figures show the linear model provides a good approximation of the relationship between embeddings and the outcomes.

5.3.2 Balance Tests

Assumption A1 requires that the BERT embeddings adequately encode the content of the patent application. This assumption implies that, conditional on embeddings, gender gaps in allowance should not be driven by any correlation between the gender of the inventors and the content of the patent, including the gender sorting into fields and classes. To test this assumption, I run an OLS regression of proxies of the content of the patent, such as technology center indicators and patent claims statistics, on various variables that describe the gender of the inventors.

Figure 6a displays the relationship between technology centers and the presence of at least one female inventor in the team, both with and without controlling for text embeddings. The gray dots present the uncontrolled relationship between mixed-gender patents and each technology center, while the blue dots show the relationship when accounting for embeddings. Although mixed-gender applications are not uniformly distributed across technology centers, text embeddings effectively account for this variation. Figures 6b, 6c display the same analysis with other measures for the femaleness of the patent application.

Accordingly, Figure 7 plots the relationship between the gender composition of the inventors' team and patent application claim statistics, such as the average and the minimum number of words per claim in all the claims and among independent claims.[19] Previous research has shown that these statistics strongly indicate the patent scope (Lanjouw and Schankerman, 2001; Marco et al., 2019). Similarly, the BERT embeddings balance the relationship between claim counts and inventors' gender.

Lastly, I test whether the results are time-sensitive, which could happen if the distribution of content changes over time. To assess that, in Appendix Figure A.4, I repeat the same balance tests separately by five-year time intervals. In line with previous findings, the patent gender is balanced across text characteristics characteristics within years.

6 Overall Gender Bias in Initial Allowance

Table 3 investigates the average observed gender disparities in initial allowance rates in the USPTO. The main analysis includes estimating OLS regressions of the form:

$$IA_i = \alpha + \beta F_i + x_i' \gamma + \epsilon_i \tag{2}$$

where F_i is a variable characterizing the femaleness of the team of inventors, and x_i is a vector of controls. Column 1 of Table 3 omits x_i, column 2 includes art-unit-year and class

[19] A claim may be written in independent or dependent form. An independent claim is a standalone claim that contains all the limitations necessary to define an invention. A dependent claim must refer to a claim previously set forth and must further limit that claim.

fixed effects, the commonly used controls in the literature to account for confounding, column 3 controls for the preferred set of 2,046 embeddings selected in Section 4.2, and column 4 includes both the embeddings and the art-unit-year and class fixed-effects. In panel (i), F_i is an indicator for having at least one female inventor, in panel (ii), F_i measures the proportion of females, and in (iii), it is an indicator for having a female ranked first or second in the inventors' list.

The raw gender gap in initial allowance between mixed gender teams and no female teams is substantial and accounts for two percentage points with standard errors of 0.0006. The initial allowance gender gap is around 25 percent of the mean no-female initial allowance rate. After controlling for the fixed effects, the gap falls to 0.35 percentage points (SE = 0.0006). Controlling for the text embeddings shrinks the gender bias to 0.001, making it statistically insignificant from zero (SE = 0.0007). The estimate does not change qualitatively when controlling for the fixed effects, suggesting robustness to omitted variables. Measuring the gender gap using the proportion of females in the inventors' team or whether a female author is ranked first or second provides similar qualitative results of zero bias when controlling the text embeddings. Appendix Table A.3 presents the same regression results using a restricted sample and comparing only female vs. no female patents teams and single author patents.

OLS is one of many types of matching estimators. With treatment effect heterogeneity, it need not coincide with other reweighting estimators. Table 4 assesses the sensitivity of my estimated mean gender gap to different reweighting schemes. Column 1 presents the unexplained component of an Oaxaca-Blinder (Oaxaca, 1973; Blinder, 1973) analysis by running a model of IA on embeddings only for the no-female applications and reports the difference between the mean men allowance rate and the fitted values for the men's regression on the mean embeddings vector of mixed gender patents. Kline (2011) shows that this estimator equals the Average Treatment on the Treated (ATT) estimator if either the propensity score or the outcome equation is linear in embeddings. Columns 2 and 3 report the Inverse probability Weighting (IPW) estimate of the ATE and ATT, estimating the propensity score for F_i with logistic regression, and Column 4 reports the Doubly Robust Machine Learning (DML) (Chernozhukov et al., 2018) partially linear regression model implemented using the Python package DOUBLEML, where initial allowance and female indicators are predicted with a neural network (NN) model.[20] DML estimator will yield

[20]The neural network's number of layers, nodes in each layer and the regularization parameter are chosen

more precise estimates without compromising consistency under an additional assumption of sparsity of the BERT embeddings in the IA and gender equations. Table 4 suggests that the mean overall gender bias is robust to the reweighting scheme, where the estimates of the gender gap in all the models are neither statistically significant from zero nor significantly different from the gender gap estimated by OLS in Table 3.

Gender Bias Over Time

The patent application data includes patent applications filed from 2001, allowing an estimation of the evolution of the gender gap over time. I do so by estimating the following OLS regression:

$$IA_i = \sum_{t=2001}^{2013} \tau_t \cdot \mathbb{1}\{\text{year}_i = t\} + \sum_{t=2001}^{2014} \beta_t \cdot F_i \cdot \mathbb{1}\{\text{year}_i = t\} + X_i'\gamma + \epsilon_i$$

where β_t, plotted in Figure 10, is the main coefficient of interest measuring the gender bias in initial allowance for the patent applications filed in year t, year_i is the filing year of application i, and X_i are the text embeddings. The blue estimates represent the uncontrolled gender gaps, documenting substantial raw gaps that fluctuated over time. The purple dots are my preferred estimates of the gaps after controlling for the text embeddings, and the green dots verify that the results are robust to the inclusion of art-unit-year and class fixed-effects as controls.

The controlled gaps show that while at the beginning of the 2000s, mixed-gender teams were significantly less likely to find their patent application initially allowed, the system-wide gender gap converged towards zero over time. Similar trends over time have also been found in the selection of Fellows of the Econometrics Society (Card et al., 2021). Conditional on achievements, the historical gender gap against women economists was substantial and significant, but it shrunk to zero between 1980 and 2010 and has become positive in recent years. It also mirrors the trends in gender discrimination in hiring decisions estimated in audit experiments (see, Schaerer et al., 2023, for meta analysis).

Gender Bias by Examiner Years of experience

Figure 11 investigates the variation in gender gaps across examiners' years of experience using my preferred model that controls for the text embeddings. Each point in the figure presents

by cross-validation.

the estimated gender bias and confidence interval by years of experience bins. Although the average gender gap in the sample is qualitatively zero, Figure 11 shows substantial heterogeneity across examiners by years of experience. On the one hand, examiners with up to 5 years of experience are significantly more likely to be biased against men, having a 0.7 to 1 percentage point higher probability of allowing patent applications with at least one female in the inventors' team. On the other hand, examiners with more than 12 years of experience are significantly more likely to be biased against mixed-gender teams.

Variation by years of experience could reflect either an age effect, such that when examiners accumulate more years of experience, they tend to be more biased against women, or a cohort effect, where different cohorts have different tastes or gender stereotypes. It could also reflect a systematic relationship between the types of patents assigned to examiners of different cohorts. I formally test these hypotheses in the following sections.

7 Variation in Gender Gap Across Examiners

Heterogeneity across examiners could either reflect the selection patterns of applications to examiners or heterogeneity in examiners' preferences. The assignment process of applications to examiners depicted in section 2 suggests that the patent content is the main instrument through which applications are assigned to examiners. In this section, I establish this assumption, which allows us to identify the examiner-level bias and characterize its distribution.

The gender bias of each examiner j is defined as the expected examination gap between applications by male and female teams with the same patent application content:

$$\beta_j = \int \omega(c)(\mathbb{E}[IA_{ij}|F_i = 0, C_i = c] - \mathbb{E}[IA_{ij}|F_i = 1, C_i = c]) dG(c), \tag{3}$$

where similar to Equation 1 integrals are taken over the distribution of the patent application content $G(c)$ in the overall population. β_j represents the tendency of examiner j's decision to vary with the gender of the inventors.

7.1 Identification

To identify the examiner-level biases, I introduce below an additional assumption regarding the nature of the assignment of patent applications to examiners.

Assumption A2. (Conditional Independence)

$$(U_{ij}, F_i) \perp Z_{ij} | C_i$$

This assumption requires that, conditional on the patent application content, there is no systematic relationship between the assignment of applications to examiners and non-text features that affect decisions, including the gender of the inventors. It does not require random assignment of examiners conditional on the text. For example, some examiners have not worked in the USPTO in all years, and therefore, the sample assignment probabilities vary by year. However, this assumption requires that after controlling for the content of the patent application, the time of assignment has no meaningful effect on the decision process. This assumption relies on the nature of the assignment process depicted in Section 2, and in the next Section, I present several tests for its validity.

Combining assumptions A1 and A2, each β_j is non parametrically identified by:

$$\beta_j = \int \omega(x)(\mathbb{E}[IA_i | F_i = 0, X_i = x, Z_{ij} = 1] - \mathbb{E}[IA_i | F_i = 1, X_i = x, Z_{ij} = 1])d(x).$$

Similar to the way I estimate the overall gender bias, my main analysis imposes further parametric assumptions and studies the distribution of the OLS coefficients on the interaction of gender and examiner indicators, and I show that similar estimates from different models of the first two moments of the distribution of β_j are robust to the functional form assumption.

7.2 Evidence for Conditional Independence Assumption

7.2.1 Balance Test

Assumption A2 implies that examiners' assignment to applications and characteristics (Z_{ij}) should not be systematically correlated with non-text characteristics conditional on the patent content. Figure 8 tests that assumption by displaying the relationship between various examiner characteristics and non-text characteristics and shows that these relationships balance after controlling for the BERT embeddings. The non-text characteristics I explore include the presence of at least one female inventor (Figure 8a), at least one Asian-named member in the inventors' team (Figure 8b), and the percentage of females in the attorney team (Figure 8c).

The first examiner characteristic in each figure is the leave-one-out mean of the initial allowance rate, which is often used in the literature to test for random assignment of judges to cases (Arnold et al., 2018; Dobbie et al., 2018; Arnold et al., 2020). The analysis also includes other examiner characteristics such as education, gender, ethnicity, and years of experience. Besides a negligible relationship between examiners with 0-1 years of experience and female examiners, I do not find any statistically significant relationship between mixed gender patents and examiner characteristics after controlling for the text embedding, even though the uncontrolled relationship is not zero. Appendix Figure A.3 verifies that the results are robust to other definitions of the femaleness of the patent application and presents the same balance tests using the share of females in the inventor team and the gender of the first or second inventors in the list of inventors.

7.2.2 Omitted Variable Bias - Long and Short Regressions

Under assumptions A1 and A2, conditional on the text embeddings, the examiner-level gender bias should be invariant to the inclusion of other non-text characteristics that are potentially correlated with examination outcome. To assess this hypothesis, I run the following "short" regression:

$$IA_i = \alpha_{J(i)} + \beta_{J(i)} F_i + X_i' \eta + \epsilon_i \tag{4}$$

and "long" regression

$$IA_i = \tilde{\alpha}_{J(i)} + \tilde{\beta}_{J(i)} F_i + X_i' \tilde{\eta} + w_i \gamma + \epsilon_i \tag{5}$$

where IA_i is an indicator for initial allowance, F_i is an indicator for mixed gender patent, w_i includes patent attorney gender, ethnicity, and experience, team size, and indicator for foreign priority, α_j and $\tilde{\alpha}_j$ are examiner fixed effects measuring examiners base leniency level, and β_j are examiner level tendency to prefer mixed-gender patents.

Under a constant effect assumption of α_j and β_j, the estimates of α_j and β_j from the short regression in Equation 4 should not be sensitive to the inclusion of the additional controls w_i.[21] Figure 9 presents the main findings. Panel (a) displays the relationship between the examiner leniency levels $\hat{\alpha}_j$, and the controls index $w_i \hat{\gamma}$ estimated in the long regression of Equation 5, and panel (b) presents the same relationship but with the examiner gender bias $\hat{\beta}_j$. $\hat{\alpha}_j$ and $\hat{\beta}_j$ were estimated in the "short" regression of equation 4, and Appendix

[21] Sensitivity to the inclusion of additional controls could also reflect treatment effect heterogeneity as additional controls change the weights of each examiner effect and examiner bias.

Table A.2 verifies that these omitted variables are predictive of initial allowance. The results suggest that examiner effects are uncorrelated with the controls index. The magnitude of each slope coefficient is tiny, where the slope coefficient for α_j is 0.0002, and the slope for β_j is -0.0002.[22]

8 Targeting the Variance

The previous section reveals a zero average gender gap together with heterogeneity across examiners' years of experience and some variation over time. In this section, I quantify this variation and measure the heterogeneity across examiners, examiners' start year, and art units. Under Assumption A1 and A2, and as long as examiners' parameters are not essentially heterogeneous with respect to the patent text, I estimate β_j by running the following fixed effect regression:

$$IA_i = \alpha_{J(i)} + \beta_{J(i)} F_i + X_i' \gamma + \epsilon_i, \tag{6}$$

where F_i is a measure of the femaleness of the patent's inventors, usually an indicator for a mixed-gender team, α_j is the examiner base-level initial allowance rate, β_j is the examiner-level gender bias, and X_i are the 2,046 text embeddings representing the patent application text. I summarise the variability of examiner level leniency and gender bias with the following target variance parameters: $\sigma_\alpha, \sigma_\beta$, the sample standard deviations of α_j and β_j, respectively, across examiners, weighted by the examiner total number of patent applications, and $Corr(\alpha, \beta) = \frac{\sigma_{\alpha,\beta}}{\sigma_\alpha \sigma_\beta}$, the correlation between examiner leniency and bias. Likewise, to quantify the share of variation driven by the start year and art units of examiners, I estimate equation 6 and the α and β parameters across examiners start-year and art units, and their respective variance components.

8.1 Estimation

I briefly review the Kline et al. (2020) leave-out estimation procedure which enables consistent estimation of the variance of β_j and α_j in the presence of unrestricted heterogeneity that

[22] This implies that the impact of a one standard deviation increase in examiner leniency on initial allowance (std=9 percentage points, presented in Table 5) may be biased by $0.09 \times 0.0002 = 0.000018$ due to omitted variables, and a one standard deviation increase in examiner gender bias on initial allowance (std=2.3, presented in Table 5) may be biased by $0.023 \times 0.0002 = 0.0000046$.

grows with the number of regressors. For further details, see Appendix C. Using a matrix representation, any variance component can be written in a quadratic form:

$$\sigma^2 = \delta' A \delta$$

where $\delta = (\alpha', \beta')'$ are the collected $\alpha = (\alpha_1, .., \alpha_J)'$ and $\beta = (\beta_1, .., \beta_J)'$ examiner level coefficients, and A is the relevant weighting matrix. Kline et al. (2020) suggest estimating:

$$\hat{\sigma}^2 = \hat{\delta}' A \hat{\delta} - \sum_{i=1}^{n} B_{ii} \hat{\xi}_i^2$$

where B_{ii} measures the influence of the ith squared error ϵ_i^2 on σ^2, $\xi_i^2 = \mathbb{V}(\epsilon_i | W_i)$ is the variance of the ith error, W_i is the matrix of all the regressors in the model including the examiner fixed effects, examiners times gender fixed effects, and the embeddings, and $\hat{\xi}_i^2$ is an unbiased estimate of ξ_i^2 derived from cross-fitting. Kline et al. (2020) provide the conditions on the W_i matrix that ensure consistency of the bias-corrected estimator. To compute $\hat{\sigma}^2$, I exploit the random projection method of Lindenstrauss (1984) when approximating $\hat{\sigma}^2$, and use a variant of the preconditioner in Koutis et al. (2011) designed to accommodate the fact that W_i includes a dense high dimensional segment of text-embeddings.

8.2 Overall Variation Estimation Results

Table 5 reports the standard deviation, correlation, and mean estimates of the examiner, start-year, and art unit level β_j and α_j effects. The standard deviation is the squared root of the Kline et al. (2020) leave-out estimate, and the correlations are the ratio of the leave-out covariance estimate and the standard deviations. In column (1), F_i is an indicator for having at least one female in the inventors' team, in column (2), it is the proportion of females, and in column (3), F_i is an indicator for having a female ranked first or second. Below, I describe the results in column (1), where the conclusions regarding the variability of gender bias are qualitatively the same across different gender definitions.

The standard deviation of α_j, presented in Panel (i), suggests substantial heterogeneity in examiners' leniency. While previous literature has emphasized the importance of discretion in the examination process (Lemley and Sampat, 2012; Frakes and Wasserman, 2017; Sampat and Williams, 2019; Farre-Mensa et al., 2020), to my knowledge, this is the first estimate of examiners' leniency after accounting for variation stemming from measurement error, and after controlling for the content of the patent. The standard deviation of α_j is 9 percentage points, which is 110% of the mean initial allowance level reported in Table 1. It implies that an application assigned to an examiner with one standard deviation higher leniency would double its chances of allowance in the first round of the examination process compared to the mean.

The standard deviation of β_j, presented in the second row of Panel (i), implies that the allowance probabilities of examiners vary substantially by the gender of the inventors. The leave-out estimate of the standard deviation of the gender bias is 2.4 percentage points, which is 29% of the mean initial allowance rate in the sample. It implies that a patent application with mixed-gender inventors assigned to an examiner with one standard deviation higher bias against mixed-gender patents would have 29% less probability to be allowed compared to an invention with the same content but male-only investors and an average leniency examiner.

Taken together, the evidence in Table 5 suggests examiner discretion and gender bias play a crucial role in allowance decisions violating both horizontal and vertical equity. First, although the probability of initial allowance is low on average, there are examiners who are likely to allow a substantial share of the applications they examine. Second, although the average examiner exhibits no bias, there is substantial variation in examiners' tastes, with some favoring patents with a mixed-gender team and others not.

The third row in Table 5 shows a strong negative correlation between examiners' bias and leniency, suggesting that lenient examiners who are more likely to allow a patent in the first round of the examination process are also more likely to be biased against women. In Section 10, I fit a nonlinear model for initial allowance and find zero correlation. It suggests, as noted in Kline and Walters (2020), that the negative correlation I find reflects a mechanical boundary effect as examiners with low initial allowance rate probability have less opportunity to discriminate. The fourth row presents the weighted average of β_j, weighted by the number of applications per examiner. I find that the average gender bias is qualitatively identical to the estimated OLS mean gender gap estimated in Table 3.

Panel (ii) presents the variance components of α_j and β_j across the 38 unique start years of examiners, spanning from 1975 to 2013. The estimated standard deviation of α_j across start-years is 3.8 percentage points, and the gender bias β_j is 1.2. Since each examiner has a unique start year, following the law of total variance, I conclude that 17% of the variation in the leniency of examiners and 25% of the variation in examiner-level gender bias is driven by variation between different cohorts of examiners. At a start-year level, I find that the negative correlation between the leniency level and gender bias is 50% stronger than the one across examiners. The strong negative correlation, together with the finding that more experienced examiners are more likely to be biased against mixed-gender patents (Figure 11) implies that experienced examiners are more lenient, as also documented in Frakes and Wasserman (2017) and was attributed partially to differences in time constraints examiners of different grade levels face.

Following the same exercise, panel (iii) presents the estimated standard deviation of α_j and β_j across 587 art units. Examiners are not entirely nested within art units because some move between art units or serve in more than one at the same time. However, since "movers" account for only 10 percent of the examiners, we can approximately state that 33% and 25% of the variation across examiners in leniency and gender bias is explained by variability across art units.

The variance component estimators are calculated from a linear model with multiple treatment margins and embedding controls. As discussed in Section 6, the OLS estimator and other matching estimators do not necessarily agree. This issue is particularly pronounced when dealing with a model with multiple treatment margins (Goldsmith-Pinkham et al., 2022). To assess the sensitivity of my results to the estimand, In Appendix Table A.4, I present the variance components of examiners' leniency and gender bias using Inverse Probability Weighting (IPW). Specifically, restricting attention to examiners with at least 100 observations, I start by estimating a multinomial logit model of the propensity score of each examiner and gender $\Pr(J(i) = j|X_i, F_i = f)$. Then, I use the IPW weights to reweight the data and estimate the variance component with the reweighted microdata. The IPW weighted variance components are qualitatively similar, with an estimated standard deviation of examiners' leniency of 9.3 and a standard deviation of the gender bias of 1.7.

8.3 Start-Year vs. Experience Effect

The evidence from Figure 11 and Table 5 suggests substantial variability in gender bias across examiners with different years of experience. Such variation could be driven by either cohort effect, in which examiners of different cohorts have different gender tastes, or by age/experience effect, in which more years of experience causes examiners to change and become more biased against mixed-gender patents. To test these hypotheses, I run the following fixed-effect regression accounting for the variation of both examiner and years of experience:

$$IA_i = \alpha_{J(i)} + \alpha_{2,exp(i)} + (\beta_{J(i)} + \beta_{2,exp(i)})F_i + X_i'\gamma + \epsilon_i \tag{7}$$

where $exp(i)$ is the number of years of experience of examiner $J(i)$ at the time of assignment to patent application i. Therefore, $\alpha_{2,exp}$ measures the leniency levels of examiners with exp years of experience, and $\beta_{2,exp}$ measures the gender bias of examiners with exp years of experience beyond the examiner levels leniency and gender tastes, measured by α_j and β_j. As noted by Abowd et al. (2002) in the context of wage models with both firm and individual fixed effects (Abowd et al., 1999; Card et al., 2013), estimation of model 7 is feasible only among the set of examiners "connected" by the same years of experience.

Table 6 reports the dispersion of the gender gap across examiners, suggesting it is cohort, rather than age/experience effects, that drives the results in Figure 11. In the first panel, I examine the stability of the standard deviation of examiner level gender gap after accounting for years of experience gender gap across the 8,335 examiners satisfying the connectivity restrictions. Comparing the standard deviation of gender bias to the one reported in Table 5, I find that controlling for examiner years of experience fixed effects has a negligible effect on the examiner level variation when F_i is an indicator for mixed gender teams (column 1) and when it is a continuous variable for the proportion female in the inventor team (column 2). Moreover, it does not impact the estimated standard deviation at all when using an indicator for female ranked first or second in the list of inventors. The estimated standard deviation of β_{exp} is modest, between 10 to 5 times smaller than the examiner level one for mixed gender and proportion female gender variables. Furthermore, the estimated variance is negative for the indicator of female ranked first or second, suggesting that this variance component is very small or zero.

The second and third panels of Table 6 provide further evidence that experience effects do not drive the variation in bias across cohorts of examiners and art units by grouping examiners by start-year and art units. Results are qualitatively similar to the examiner-level analysis. Accounting for the years of experience fixed effects has almost no impact on the variability of gender bias across start years and a moderate effect on the estimated variability across art units when measuring the femaleness by the proportion of females. Taken together, these results establish that the variability in gender bias across examiners with different years of experience is driven mainly by cohort effects, where different cohorts of examiners have different preferences towards the gender of the team of inventors.

8.4 Characterizing Biased Examiners

The analysis so far establishes that gaps in initial allowance vary substantially across examiners. To further describe the type of examiners that exhibit bias, I report the coefficients from regressions of $\hat{\beta}_j$ from equation 6 when F_i is an indicator for mixed gender patents, on various examiner characteristics. While such relationships do not necessarily describe a causal effect of examiner attributes on gender bias, they offer a summary of which examiners are more likely to exhibit bias. Since bias varies across technologies and art units, I describe both the cross-sectional relationship across all examiners and the within-art-unit relationship of examiners' attributes and bias.

Table 7 reports the main results. Columns 1-5 present the estimated coefficient from a regression of estimated gender bias on one characteristic: whether the examiner holds a Ph.D. or higher degree, female examiner, Asian examiner, years of experience, and the share of mixed gender patent applications in the USPC class. Column 6 presents the coefficients from a regression where all the covariates are included simultaneously. Finally, column 7 presents the estimated coefficients in a regression that includes art unit fixed effects.

Female examiners and examiners holding a Ph.D. are more likely to be biased against men, while there is no correlation between the bias and examiners with Asian names. Furthermore, in line with the results from the previous section, examiners with more years of experience are more likely to be biased against mixed-gender patents. Lastly, I find that the higher the share of mixed-gender patents in the USPC class, the less likely the examiner is biased against mixed-gender patents. Column (6) reveals that most of these relationships persist when controlling for all the covariates simultaneously, besides the coefficient on examiner education and Asian examiners.

The relationship between gender bias and other examiner and application characteristics within are-units differs from the cross-sectional relationship. On the one hand, I find that the negative relationship between years of experience and gender bias is robust to including other characteristics and art unit fixed effects. On the other hand, there is no clear relationship between examiners' gender and bias within art units. Lastly, I find that while the cross-sectional relationship between the share of mixed-gender teams and bias is positive, it is negative and twice as large within art units. This pattern is consistent with the finding in

Breda and Ly (2015) that male-dominated fields in the entrance exam for French higher education were biased in favor of women.

8.5 Within-Group Variation

There is substantial variation in leniency and gender bias across examiners, and that bias is correlated with various examiner characteristics. Next, I study whether the second moment varies by examiners' attributes, such as gender, start year, and time.

Examiner gender

Table 8 displays the estimated means and standard deviations of the gender gap separately by the gender of the examiner. The first panel presents the estimate of β, the average gender gap, estimated in equation 6 separately by examiners' gender.[23] The first row presents the raw gender gap without controlling for the text embeddings, and the second row presents my preferred estimate for the average gender gap, accounting for the text embeddings. The first panel reveals two facts. First, the raw gender gap varies by the gender of examiners, with a gap among male examiners twice the size of that among female examiners. These differences could reflect either gender differences in bias or differences in the distribution of examiners and applicants across fields and genders. Second, while the controlled gender gap in the full sample is statistically insignificant from zero, on average, male examiners are 0.2 (SE = 0.001) percentage points less likely to initially allow a patent by mixed-gender teams. In contrast, the point estimate for the gender bias of female examiners is very small in magnitude, positive, and statistically insignificant. The estimates for the set of examiners with non-classified names are similar to the ones among the male examiners.

The second panel of Table 8 suggests substantial variability within examiner gender. Not only are female examiners less biased on average, but they also use less discretion and have much lower levels of variability in gender bias. The standard deviation of the leniency of female examiners is 7 percent, 72% of the standard deviation of the leniency levels of male and unknown examiners. The standard deviation of the gender gap among female examiners is only 1.3 percent, half of the standard deviation of the gender gap among unknown examiners.

[23] This table uses F_i and an indicator for mixed-gender team. See Appendix tables A.5 and A.6 for the equivalent exercise with F_i being the share of female inventors and an indicator for having at least one female in the team of inventors.

Taken together, I conclude that female examiners are substantially less likely to be biased, thereby posing less risk for bias in the system.

Within examiner start year variation

Different cohorts of examiners differ not only in their average preferences towards the gender mix of inventors but also in the probability of posing extreme levels of gender bias. In Figure 12, I study that phenomenon by estimating the within start-year bins variance component of α_j and β_j when the femaleness of the patent is measured by whether there is at least one female in the team of inventors and by the proportion of females in the inventors' team. The pink "X"s are the estimated standard deviation of α_j, and the blue dots are the estimated standard deviation of β_j.

The Figure shows that the younger cohorts of examiners that joined the USPTO after 2003 have lower levels of variability in discretion and bias. Their standard deviation of discretion is almost 50% lower than the older cohorts, and the standard deviation of gender bias of the 2008+ cohort is around 40% of the standard deviation of the examiners that joined in 2000-2002. Using an indicator for mixed-gender patents reveals a slightly different story than when measuring the femaleness of the patent using the share of female inventors. The first presents stable behavior across the cohort that joined before 2000, and the latter suggests that the very old cohort was less variable. Taken together with the evidence from Section 8, I conclude that younger cohorts pose less risk in the system and are biased in favor of women.

Within year variation

The average gender bias decreased over time and converged to zero. This leads to the follow-up question: does the risk of encountering a biased examiner also change accordingly? To test that, Figure 13 plots the standard deviations of β_j within bins of 3 to 4 years. To assess the trend in discretion over time, Figure 13 additionally plots the estimates of the standard deviation of α_j.

Although the average gender bias converged to zero over time, the variability in discretion and bias increased by almost 100%. Considering, in addition, the finding in Table 6, we can conclude that these trends are driven by the change in the composition of examiners over time. The new young examiners are more likely to agree with each other but have different gender preferences than the senior ones. As a result, the polarization in preferences for gender among examiners has increased. This result reflects an increasing uncertainty regarding the outcome of the examination process.

9 Robustness and Mechanisms

9.1 Rejection Reasons

To further investigate the underlying roots behind initial rejections, I utilize the "USPTO Office Action Rejection data set" which covers the universe of mailed office actions and grounds for rejections from 2008 to 2017. A typical Non-Final Rejection Office action by an examiner identifies the specific claims and the statutory or nonstatutory grounds on which those claims are objected to and/or rejected. Examiners can reject a patent on the following grounds: a 101-rejection, which reflects a violation of eligibility, double patenting, or lack of usefulness and credibility; a 102-rejection, which reflects a lack of novelty; a 103-rejection, which reflects a lack of obviousness; and a 112-rejection, which describes failure to meet the requirements regarding the adequacy of the disclosure of the invention.

For every rejection ground category, I generate four indicators, one for each rejection ground, which equals one if the patent application was rejected at the first round or examination on the basis of that category. Notably, a rejection could have multiple grounds, and each ground could relate to more than one claim. As discussed in Frakes and Wasserman (2017), rejections based on lack of novelty and obviousness are typically viewed as more time-consuming as they require a delicate prior art search and prior art comparison.

Table 9 presents the rejection reasons analysis. Panel (i) presents the coefficient from an OLS regression of an indicator for rejection reason on an indicator for mixed gender team of inventors on the sample of patent applications filed after 2008. The first row displays the uncontrolled gender gap, and the second row the gender gap after controlling for the patent text embeddings. Interestingly, the raw gap in obviousness and novelty rejection reasons is very small and indistinguishable from zero. These are the most prevalent rejection types that require effort and prior art search from the examiners. In contrast, on average, mixed-gender patents are more likely to be rejected because of lack of eligibility and writing - less common and simpler rejections. In line with previous findings, the second row of Panel (i) shows that the average gender gap disappears after controlling for the patent application text.

To determine whether there are rejection reasons that are more likely to serve as grounds for rejection among biased examiners, I run the following stacked regressions together, clustering the standard errors by application id:

$$\begin{aligned} IA_i =& \alpha_{J(i)} + \beta_{J(i)} F_i + X_i' \gamma + \epsilon_i \\ IR_i =& \alpha^R_{J(i)} + \beta^R_{J(i)} F_i + X_i' \gamma^R + \epsilon^R_i. \end{aligned}$$

The first equation is identical to the main regression I present in previous sections. In the second equation, IR_i is an indicator for the reason of rejection, α^R_j measures the inclination of examiner j to initially reject on the ground of reason IR, and β^R_j measures the extent to which examiner j is more likely to reject all male vs. mixed gender patents based on that ground. With the estimates of gender bias β_j and β^R_j, I estimate the variance-covariance matrix of the joint distribution of (β_j, β^R_j). For detailed information on the estimation, see Appendix Section C.[24]

Panel (ii.a) of Table 9 reports the corresponding estimated standard deviations and correlations. The standard deviation of the gender gap in initial allowance in 2008-2013 is 2.8 percentage points, slightly higher than the one in the full sample, reflecting the increase in bias variability over time I document in Figure 13. The standard deviation of gender gap by rejection reason is around four percentage points, reflecting the higher base-level rejection rates. Also, as expected, there is a strong negative correlation between gaps in initial allowance and gaps in all the rejection reasons.

Estimates of the variance-covariance components of the examiner gender gaps in initial allowance and rejection reasons can be used to estimate the coefficients from the infeasible OLS regression of initial allowance gender gap on rejections gender gaps:

$$\beta_j = \delta_0 + \delta_1 \beta^R_j + u_j,$$

where the δ_1 coefficient is a function of the variance components, i.e., the ratio of the covariance between β_j and β^R_j and the variance of β^R_j. Given these estimates, I calculate the implied R^2 from this regression that measures the share of gender bias variability in initial allowance that is explained by bias in each rejection reason. If a biased examiner chooses the

[24]Lachowska et al. (2022) run similar seemingly unrelated regressions with employer-employee data measuring the covariance between firm effects on wages and hours in Washington.

rejection reason proportional to the prevalence of each rejection reason, then the R^2 should be proportional to the likelihood of each rejection reason. In contrast, if they are more likely to use a particular rejection ground when performing a biased assessment, the proportions should not align with the distribution of rejections.

Panel (ii.b) in Table 9 presents the implied OLS δ_0 coefficient and R^2 from the infeasible regression mentioned above, revealing that biased examiners are disproportionally more likely to perform writing-based rejections. The gender gaps in rejections based on obviousness (103) and writing (112) explain most of the initial allowance gender gap variability, accounting for 25 and 30 percent, respectively, of the variance of β_j. However, these rejections are not equally likely. Rejections based on obviousness are the most prevalent, accounting for almost 70 of the rejections in the first round of examination, being twice more likely than writing-based rejections.

Taken together, these indicate that biased evaluations are more likely to be based on writing. This result aligns with the reasoning that such rejections are "simpler" because they require less effort than prior-art-based rejections. A similar pattern was identified in Frakes and Wasserman (2017), in which examiners facing more time restrictions had a lower probability of performing obviousness rejections.

9.2 Other Non-text Characteristics

The objective of this paper is to estimate the gender bias parameter defined in Equation 3. As explained in Section 5, this parameter captures both disparate treatment and disparate impacts that are uncorrelated with text characteristics. To assess the extent to which other non-text patent characteristics, such as inventors' ethnicity and lawyer characteristics, translate into gender disparities, I rerun the main analysis, including other non-text characteristics. First, I re-estimate Equation 2, adding each of these covariates one at a time: (i) representing the presence on the application of at least one inventor with a foreign name, i.e., one not appearing in the SSA name tables; (ii) an indicator for the presence of at least one Asian in the inventors' team; and (iii) the years of experience of the attorney's office.[25]

Panel (i) of Table 10 suggests that the mean over gender bias estimates are robust to the inclusion of other non-text characteristics. Column 1 replicates the results from Table

[25]See Appendix B for further detail on variable construction.

3, and columns 2-5 report the coefficients from a regression that includes an additional non-text characteristic. Including other non-text characteristics does not affect the measures of the gender gap in initial allowance. Moreover, I find no average allowance gap by inventor ethnicity or attorney's gender. Contrarily, however, the lawyer's years of experience are positively related to the initial allowance even after controlling for the patent application text. That could reflect either the causal effect of experienced law companies on the application process beyond their effect on writing or examiners' preferences towards more established law companies.

Second, Panel (ii) reports the variance components from the following fixed-effect regression

$$IA_i = \alpha_{J(i)} + \beta_{J(i)} F_i + \eta_{J(i)} w_i + X_i' \gamma + \epsilon$$

where w_i is the additional non-text characteristics and η_j measures the variation in examiners tastes with respect to characteristic w_i. Then, Panel (ii) displays the standard deviation and correlation of (β_l, η_j) using the estimates $\hat{\beta}_j$ and $\hat{\eta}_j$. Echoing the results from Panel (i), the variance of gender bias is unaffected by the inclusion of other characteristics. I find that examiners exhibit variation with respect to these other characteristics comparable to the variability in gender bias, but the correlation between gender bias and these other biases is very low, amounting between 1 to 6 percent.

10 The Cost of Variance in Bias

The analysis conducted thus far has shed light on the prevalence of gender bias during the first round of the application examination process. Next, I turn to explore the broader implications of such bias and its potential effects on economic outcomes. Extensive research has demonstrated the significant contribution of innovation, including the acquisition of patents, to the success of firms and inventors (Kogan et al., 2017; Kline et al., 2019). In this section, I study the consequences of bias on economics outcomes by estimating the distribution of examiners' behavior and how it translates into differences in patents' stock market return as measured by Kogan et al. (2017)

Identification of the effect of bias on market return is challenging. Unlike the first round of the application process, Subramani et al. (2021) find that women are less likely to persist and resubmit their patent application if initially rejected. Hence, a gender gap in outcomes of granted patents could also reflect differences in the females' behavior rather than the examiners'. In addition, market return is observed only for granted patents assigned to publicly traded firms, introducing a sample selection. To address this concern, this section adopts a sample selection correction approach inspired by the Heckman selection model (Heckman, 1979) exploiting examiners as instrumental variables, conditional on the patent text. I model the examiner's decision parametrically as a single index model and use that model to simulate different counterfactuals of examiners' behavior. Since examiners directly affect the outcomes of rejected patents by restricting the scope of their claims and adding prior art citations, I restrict attention to patents that were initially allowed, thereby not violating the exclusion restriction assumption.

10.1 Examiners' Decisions

I start with structurally modeling the initial allowance decision of examiners from Section 5.1. I assume examiners form an accurate posterior mean prediction, $E[q_i|\epsilon_{ij}, C_i, F_i = f]$, of the patent quality q_i given the available information on patent content C_i, the gender mix of the inventors F_i, and the noisy signal ϵ_{ij}. To make an allowance decision, each examiner compares the posterior mean quality to the subjective cost, $\tau_j(C_i, f)$, for allowing a patent with gender $F_i = f$ and content C_i. Thus, this model yields the following decision rule:

$$\begin{aligned} IA_{ij} &= \mathbb{1}\{E[q_i|\epsilon_{ij}, C_i, F_i = f] \geq \tau_j(C_i, f)\} \\ &= \mathbb{1}\{\mu(C_i, f) + u_{ij} \geq \tau_j(C_i, f)\} \end{aligned} \tag{8}$$

Taste-based gender bias, as in Becker (1957), arises when examiners perceive differing social costs from allowing patents with different mixed-gender teams but the same expected posterior quality by applying different posterior quality thresholds by gender. Models of inaccurate stereotyping can result in observationally equivalent bias (Arnold et al., 2018; Bohren et al., 2022). Statistical discrimination as modeled in Aigner and Cain (1977) arises when gender affects examiners' posterior mean prediction of the patent quality due to differences in the prior distribution of patent quality by gender. As detailed in Section 5, all these models would produce an observed mean allowance gender gap for which $\Pr(IA = 1|C_i, F_i = 0) \neq \Pr(IA = 1|C_i, F_i = 1)$.

For every patent application, I model the potential log market return $R_{ij}(d)$ of patent application i with inventors' gender mix F_i and patent content C_i that was examined by examiner j as a function of whether the patent application was initially allowed $d \in \{0, 1\}$:

$$R_{ij}(IA_{ij}) = \psi_c(C_i, F_i)IA_{ij} + \delta_{cj}(C_i, F_i)(1 - IA_{ij}) + \omega_{ij} \tag{9}$$

Note that the expected market return among initially rejected patents is affected by the identity of the examiners because examiners can restrict the scope of the patent by requesting amendments to the patent claims and demanding the inventors cite additional prior art. However, among patents that were allowed in the first round of the patent application, there is no direct examiner causal effect. Therefore, the expected market return of firms assigned to initially allowed patents:

$$E[R_{ij}|F_i, C_i, J(i) = j, IA_{ji} = 1] = \psi_c(C_i, F_i) + E[\omega_{ij}|F_i, C_i J(i) = j, IA_{ij} = 1] \tag{10}$$

where $E[\omega_{ij}|F_i, C_i, J(i) = j, IA_{ij} = 1]$, is the expected unobserved market return among initially allowed patents that were assigned to examiner j and whose inventor gender is F_i. If examiners' perceived quality is uncorrelated with observed market return ($Cov(\omega_{ij}, u_{ij}) = 0$), then I could estimate Equation 10 by running an OLS regression. Otherwise, $E[\omega_{ij}|F_i, C_i, J(i) = j, IA_i = 1]$ is the *control function* that summarizes the selection bias. Note that finding that $\psi_c(C_i, 0) \neq \psi_c(C_i 1)$ need not signal bias unless we think that examiners seek to maximize market return (Canay et al., 2020). In any case where $q \neq R$ and q and R are not very strongly correlated, it is possible that the average patents by mixed-gender authors have different market returns, while $\Pr(IA = 1|C_i, F_i = 0) \neq \Pr(IA = 1|C_i, F_i = 1)$ so applications by different gender-mix of authors receive the same treatment. Such disparities in market return conditional on patent content could reflect, for example, differences in the firms male and female authors work at or differences in how male and female inventors translate their inventions into valuable products.

The joint distribution of (u_{ij}, ω_{ij}) is modelled as jointly normal:

$$\begin{pmatrix} u_{ij} \\ \omega_{ij} \end{pmatrix} | F_i = f \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho\sigma \\ \rho\sigma & \sigma^2 \end{pmatrix}\right)$$

where ρ captures the extent to which examiners' decisions are correlated with patents' market return. When $\rho > 0$, market return is correlated with the measure of quality perceived by examiners. In that case, among examiners who are biased against females, the mean market return of patents by mixed-gender teams would be lower than their mean market return had these patents been judged as males' patents, the opposite will be true among examiners who are biased against all-male patents.

Identification: Selection models without excluded instruments are only identified by functional form restrictions (Heckman, 1990). Therefore, following the findings in Section 5.3, I treat examiners as instruments that shift the probability of allowance without directly affecting the market return of initially allowed patents. Formally, identification requires the following assumptions: Relevance, exclusion, and monotonicity. The validity of the first two assumptions has already been established in the previous sections. I find that examiners' discretion plays a significant role in the allowance decision and that, conditional on the patent application content, examiners' assignments are as good as random. Also, since I estimate the model only among initially allowed applications, examiners, by construction, have no direct causal effect on market return.

The third assumption, monotonicity, requires formally that for every pair of examiners j and ℓ, either $\Pr(IA_{ij} = 1) \geq \Pr(IA_{i\ell} = 1)\ \forall i$, or $\Pr(IA_{ij} = 1) \leq \Pr(IA_{i\ell} = 1)\ \forall i$. In fact, this is a weaker assumption of the well-known strict monotonicity assumption by Imbens and Angrist (1994). Strict monotonicity does not allow for random violation of the common ordering that could arise when $u_{ij} \neq 0$. This relaxation of the strict monotonicity was introduced in Frandsen et al. (2023), allowing random violation in monotonicity as long as u_{ij} have the same variance for all examiners.

Conceptually, the monotonicity assumption requires that examiners agree on the ranking of applications on average, thereby imposing restrictions on the underlying behavioral model and skills of examiners. To relax this assumption, I allow the preferences of examiners to vary across patent applications by inventors' gender and by the content of the patent $\tau_{jf}(x_i)$. By doing so, I allow examiners to rank patents with different content differently, requiring monotonicity only among applications with the same gender and patent content.

Rather than controlling for over 2,000 text embeddings, I control for a lower dimensional representation of the patent content to relax the monotonicity assumption, and in the next section, I explain how I leverage the propensity score from Section 8.2 to reweight the maximum likelihood so it accounts for embeddings. I use the first two components of the UMAP dimensionality reduction presented in Figure 3, which I denote by $\tilde{x}$. Therefore, the random thresholds and the parameters in the market return and initial allowance equation are modeled as follows:

$$\begin{aligned}
\mu_(\tilde{x}_i, F_i) &= m_0 + \tilde{x}_i' m_{0x} + (m_1 + \tilde{x}_i' m_{1x}) F_i \\
\tau_j(\tilde{x}_i, F_i) &= \tau_{0j} + \tilde{x}_i' \tau_{0xj} + (\tau_1 + \tilde{x}_i' \tau_{1xj}) F_i \\
\psi(\tilde{x}_i, F_i) &= \psi_0 + \psi_1 F_i + \tilde{x}_i' \psi_x,
\end{aligned}$$

where $\tilde{x}$ is normalized to mean zero with a standard deviation of one. Note that I do not control additively for the full set of patent text embeddings but only the first two UMAP components. Therefore, I explain next how I reweight my likelihood using the propensity score from section 8.2 to control for the full patent content.

Likelihood: Define $\theta_j = (\tau_{0j}, \tau_{1j}, \tau_{0xj}', \tau_{1xj}')$. For every patent application i assigned to examiner $J(i)$, I define the following probabilities:

$$\begin{aligned}
p_i(\theta_{J(i)}) &= \Pr(IA_{iJ(i)} = 1 | F_i, \tilde{x}, \theta_{J(i)}) \\
f_i(\theta_{J(i)}) &= \Pr(R_i = r | IA_i = 1, F_i, \tilde{x}, \theta_{J(i)})
\end{aligned}$$

where $p_i(\theta_j)$ is the probability of initial allowance, and $f_i(\theta_j)$ captures the probability density of observing $R_i = r$ for initially allowed patents. Let $I_j \equiv \{i : J(i) = j\}$ be the set of applications that were assigned to examiner j. The likelihood of observing $\{IA_i, R_i, F_i, \tilde{x}_i\}_{i \in I_j}$ for the patent applications assigned to examiner j is

$$l_j(\{IA_i, R_i, F_i, \tilde{x}_i\}_{i \in I_j} | \theta_j) = \prod_{i \in I_j} (1 - p_i(\theta_j))^{1 - IA_i} \cdot f_i(\theta_j)^{IA_i}.$$

I account for differences in patent content beyond the first two UMAP components by reweighting my likelihood to match the distribution of examiner-gender characteristics. I begin with the propensity scores $ps_{ij} = \Pr(J(i) = j, F_i = f | C_i)$ from Section 8.2. Then, I normalize the weight of each application in two steps. In the first step I normalize $w_{ij} = (\frac{1}{ps_{ij}}) / (\sum_{i \in I_j} \frac{1}{ps_{ij}})$ to sum to one within each examiner. Then, to hold the number of applications per examiner constant, I form the adjusted weights:

$$\tilde{w}_{ij} = w_{ij} \times N_j$$

where N_j is the total number of applications assigned to examiner j. Therefore, the likelihood of observing $\{IA_i, R_i, F_i, \tilde{x}_i\}_{i \in I_j}$ for the applications assigned to examiner $J(i) = j$ is:

$$l_j(\{IA_i, R_i, F_i, \tilde{x}_i\}_{i \in I_j} | \theta_j) = \prod_{i \in I_j} \Bigg[(1 - p_i(\theta_j))^{1 - IA_i} \cdot f_i(\theta_j)^{IA_i} \Bigg]^{\tilde{w}_{ij}}.$$

This content-adjusted likelihood ensures that examiners with more applications have more influence on the estimation, which aligns with my estimation strategy of the variance components in Section 8. A similar reweighting approach was taken in Chan et al. (2022).

I treat the examiner-level thresholds θ_j as draws from a prior normal distribution with mean zero and variance-covariance matrix Σ:

$$\theta_j \sim \mathcal{N}(0, \Sigma).$$

Finally, the log-likelihood of the data given the parameter vector $\Theta = (\mu_0, \mu_{0x}, \mu_1, \mu_{1x}, \psi_0, \psi_x, \psi_1, \Sigma)$ is:

$$\mathcal{L}(\Theta | IA_i, R_i, F_i, C_i) = \sum_j \log \int_\theta l_j(\{IA_i, R_i, F_i, \tilde{x}_i\}_{i \in I_j} | \theta_j) f(\theta_j | \Theta) d\theta_j,$$

where the integral is computed using simulated maximum likelihood.

10.2 Results

Table 11 presents the main parameter estimates of Θ. Panel (i) displays the estimates for the initial allowance regression. μ_0 represents the mean initial allowance rate for all-male patent applications and μ_1 the differences between all-male and mixed-gender. In line with my findings using a linear model, the estimate of μ_1 is very small and insignificant from zero, suggesting that there is no average difference in allowance probability between mixed-gender and all-male patent applications.

Panel (iii) presents the variance of examiners' allowance thresholds, where σ_0 represents the base-level variability in allowance decisions of examiners, and $\sigma_{\lambda 1}$ describes the extent to which examiners' allowance threshold is different between all-male vs. mixed-gender patent applications, i.e., the variability in gender bias. Translating the $\sigma_{\lambda 1}$ to allowance probability Table 11 implies that the variance of gender bias for the average patent text is 0.022, which accords with the findings in Table 5. Moreover, I find that the correlation between λ_1 and λ_0 is zero, suggesting that the negative correlation I found in Table 5 reflected a mechanical boundary relationship.

Panel (ii) presents the estimates of the log market return equation conditional on initial allowance and after correcting for selection bias, where ψ_0 describes the mean market return on all-male patents and ψ_1 describes the difference between all-male and mixed-gender inventor teams. On average, mixed-gender patents generate 247 thousand dollars higher market return than no-female patents with equivalent patent content and text. This disparity could reflect the differences in productivity of the firms female inventors work at or the productivity of the teams female inventors participate in.

Nevertheless, even if mixed-gender patents generate more valuable inventions for firms, mean zero gender bias together with positive variance don't necessarily imply that the behavior examiners generate inefficiencies. Variance in bias generates lower total market return value if the objectives of examiners, i.e., the object they maximize, need to be correlated with market return. This aspect is evident from the estimate of ρ in panel (iv), which shows that the correlation between initial allowance decision and market returns is 0.1 (SE = 0.004). The finding that the decision of examiners is moderately positively correlated with economic outcomes aligns with the findings of Matcham and Schankerman (2023) who model the full screening and renegotiation decisions of examiners and applicants.

10.3 Counterfactuals

I evaluate the economic implications of positive variance in bias together with mean zero gender bias via a simulation exercise. Using the parameters in Tables 11, I simulate a set of 6,000 examiners, each examining 1,500 applications with an average patent text embedding value, enforcing 15% mixed of the teams to be mixed-gender teams. I evaluate the impact of bias and discretion on stock market return using two counterfactual exercises. In both, I compare the status quo distribution of examiner behavior in which examiners exhibit substantial discretion and mean zero gender bias together with positive variation in bias. I compare the status quo to two scenarios. The first considers a new initial allowance decision rule that maintains the same examiner-level initial allowance rate, therefore allowing for examiner heterogeneity in leniency, but enforces uniform zero gender bias for all the examiners. Formally, for every examiner j, I find the scalar $\tilde{t}_j$ such that

$$\Pr(u_{ij} \geq \tau_{j0} - \mu_0 + (\tau_{j1} - \mu_1)F_i) = \Pr(u_{ij} \geq \tilde{t}_j).$$

The second scenario considers the initial allowance decision rule in which there is no discretion across examiners. To maintain the same total number of applications accepted across counterfactual simulations, I set the examiner threshold to be the one that attains the same baseline rate of initial allowance. Then, for every scenario, I report the stock market return of initially allowed patents, where the main focus is on the compliers, i.e., those applications that were not allowed in the status quo but are allowed under the counterfactual exercise and the opposite. If the total stock market return of the first is greater than the second, I conclude that the observed levels of discretion generate economic loss.

Variation in bias and discretion generates a substantial economic loss, as reported in Table 12. Panel (A) reports the evaluation of uniform zero bias. It shows that 1.1% of the female applications would have been affected by the zero variance policy, increasing on average by 179 thousand dollars the stock market return of each patent application. Among all male applications, 0.22 percent would be affected by the policy, resulting in an average increase of 4,300 dollars per application. With an average of 40,000 patent applications assigned to publicly traded firms a year and an average of 8.5% initial allowance rate, column (4) shows the total loss in stock market return amounts to 1.4 million Dollars for female patents and 299 thousand Dollars for all male patents a year. This total cost of 1.7 million Dollars per year reflects only a lower bound of the social cost of positive variance of bias because the future evaluates only the loss of applications in the first round of patent applications. Under the assumption that examiners' behavior in the first round of the examination process and in later rounds follow the same distribution, column (5) shows that this total cost reaches 12.6 million Dollars per year for eventually granted patents.

The economic cost from any examiner's discretion is almost six times larger. In Panel B, I report the mean market return of compliers, comparing the status quo to no discussion scenario. The share of compliers is higher under this exercise. However, since I enforce a symmetric distribution of discretion, the average market return loss per patent application is identical to the one found in Panel A. The larger share of compliers eventually results in a total loss of 10.15 million Dollars per year among initially allowed patent applications and a total of 76.6 million dollar loss per year for eventually granted patent applications. To have a sense of this magnitude, it amounts to 31% of the value of the median public US firm in 2013.

11 Conclusion

Women are underrepresented in the patent system. Yet, the extent to which observed disparities arise from discriminatory practices is unclear. To shed light on this, this study adopts a novel identification strategy and analyzes the gender gap in the first round of the examination process conditional on the patent application text. This paper finds that while the average gender bias is zero, it masks substantial heterogeneity across examiners, where some examiners are biased against women and some others are biased in favor of women. The start-year of the examiner explains 25 percent of the variance of gender bias, where senior examiners are more likely to be biased against mixed-gender patents, and young examiners are more likely to be biased against no-female patents. Lastly, studying the dynamics over time, I find that, on average, the system evolved from being discriminatory against women in the years 2001-2003 to being unbiased on average. However, due to the changes in the cohort composition of examiners, that variance in gender bias has increased over time, reflecting an increase in the risk of encountering an abnormally biased examiner.

Much of the discrimination literature primarily fixates on average gaps, which map only partially to fairness and inefficiencies. Firstly, even though there is no ex-ante bias, heterogeneity in bias undermines ex-post horizontal equity where patents of equivalent quality but different inventor team compositions experience disparate odds of approval. Secondly, an exclusive focus on mean bias overlooks the detrimental effects of misallocation, which may manifest even if the mean bias is zero. Utilizing Kogan et al. (2017)'s stock market return model for patents, my analysis estimates the lower bound of the annual cost of having a positive variance in gender bias among initially allowed patent applications assigned to publicly traded firms to be approximately \$1.67 million. Extrapolating the implied cost for granted application, I report that bias generates a loss of 12.6 million Dollars per year. Finally, I estimate the cost attributable to all the forms of examiner discretion to be 76.6 million Dollars per year (31% of the value of the median public US firm in 2013).

This paper suggests that a critical re-evaluation of the patent examination process is needed, particularly with respect to examiners' access to the names of the inventors. To counter the influence of discretion and bias in patent examinations, implementing blind reviews, possibly accompanied by other computer-based methods, could provide potential remedies.

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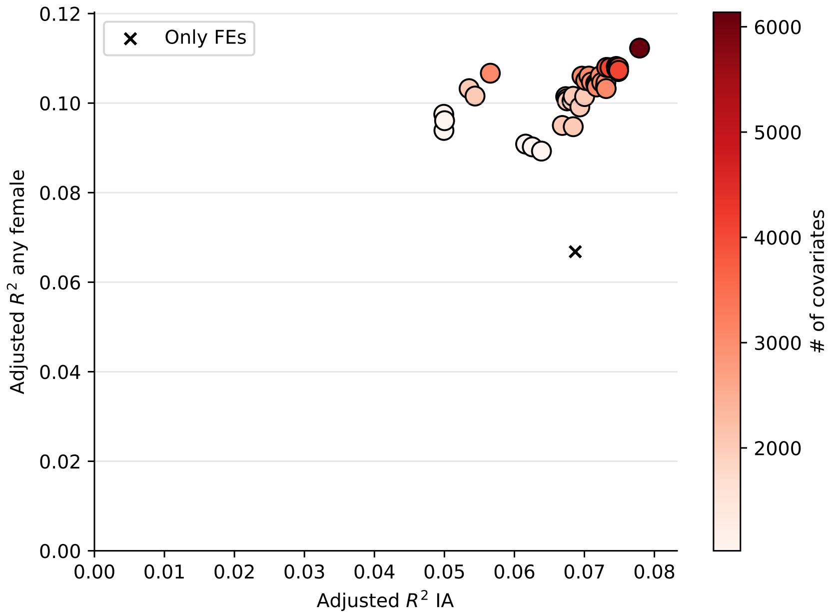
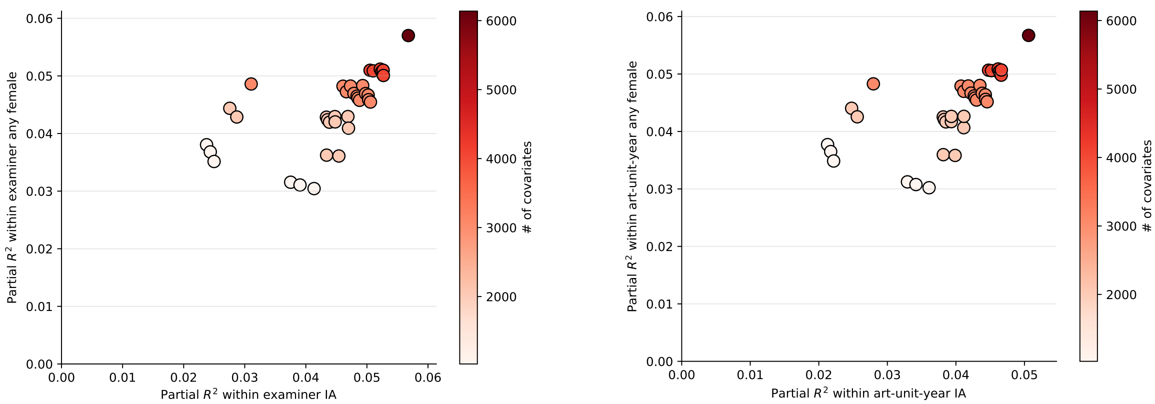
Figures

Figure 1: Adjusted R^2 of initial allowance and any female indicator on patent text embeddings



Note: This Figure plots the adjusted R^2 from regressing initial allowance (the horizontal axis) and mixed gender team indicator (the vertical axis) on different combinations of text embeddings. Different dots in the Figure represent different combinations of the embedding layers and different embedding representations of the patent's claims and the patent's description section. Section 4.2 provides information on the embeddings layer, and the exact point estimates generating this Figure are available in Appendix Table A.1. Darker dots represent a model with more covariates, and the "X" symbol represents the adjusted R^2 for a model with art-unit-year and class fixed effects, which includes more than 8,000 fixed effects.

Figure 2: Partial adjusted R^2 of initial allowance and any female indicator on patent text embeddings

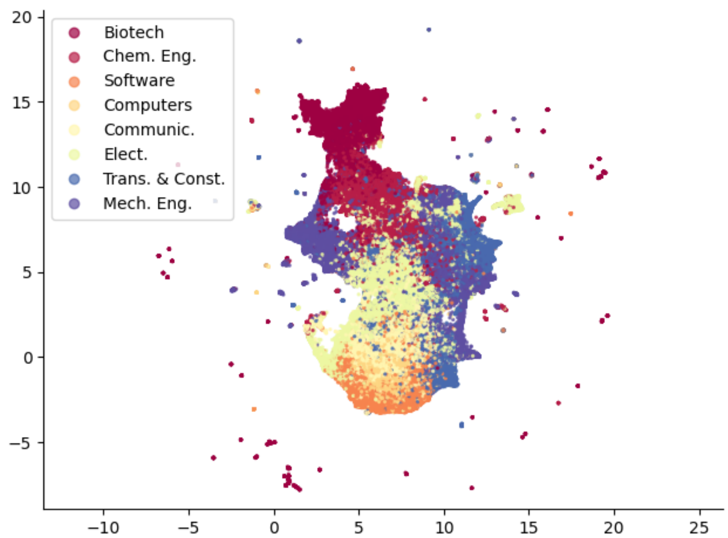


(a) Within examiner

(b) Within art-unit-year class

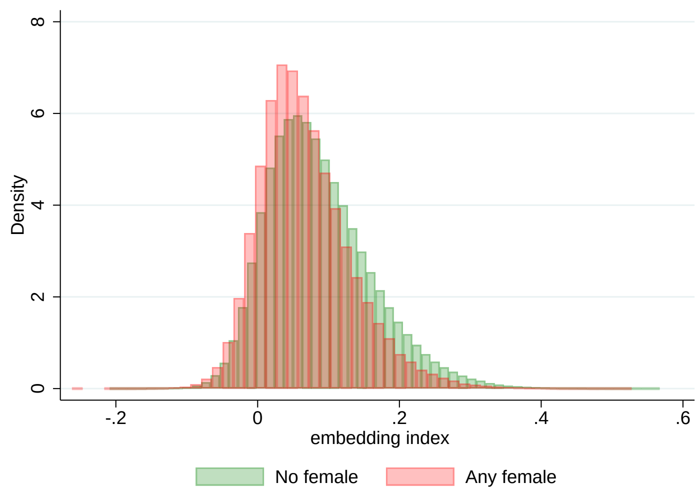
Note: This Figure plots the partial adjusted R^2 from regressing initial allowance (the horizontal axis) and mixed gender team indicator (the vertical axis) on different combinations of text embeddings. Sub-Figure (a) measures the predictive power of embeddings within examiners, and Sub-Figure (b) measures the predictive power of embeddings after controlling for art-unit-year and class fixed effects. Different dots in the Figure represent different combinations of the embedding layers and of the embedding representations of the patent's claims and the patent's description section. Section 4.2 provides information on the embeddings layer and the exact point estimates generating this Figure are available in Appendix Table A.1. Darker dots represent a model with more covariates

Figure 3: UMAP visualization of the patent text embeddings by technology centers



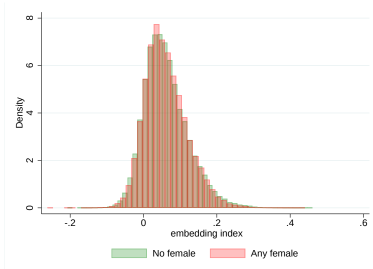
Note: This Figure plots the Uniform Manifold Approximation and Projection (UMAP) McInnes et al. (2018) visualization of patent text embeddings and its relationship with patent technology centers. The Figure was generated using a random sample of 30% of the patent application. Different colors represent different USPTO technology centers.

Figure 4: Histogram of embeddings index by the gender mix of inventors

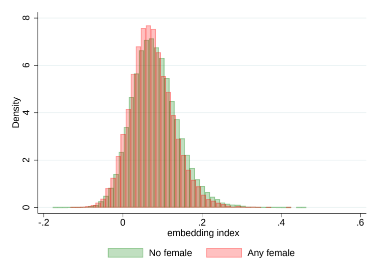


Note: This Figure plots the distribution of the embedding index separately for patent applications written by mixed-gender patents and by teams with no female inventors. To generate this Figure, I estimate an OLS regression of the form $IA_i = \alpha + \beta F_i + C_i'\gamma + \epsilon_i$ where IA_i is an indicator for initial allowance, F_i is a mixed gender team indicator, and C_i are my preferred 2,046 text embeddings. The embedding index is the estimated linear combination $C_i'\hat{\gamma}$.

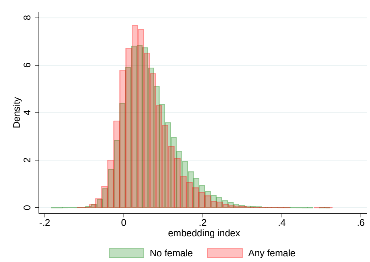
Figure 5: Histogram of embeddings index by gender and technology center



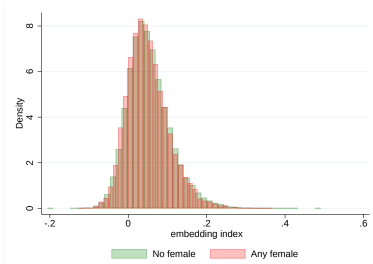
(a) Biotechnology (16)



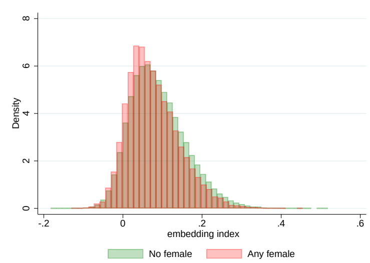
(b) Engineering (17)



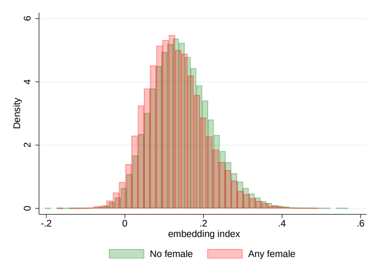
(c) Software (21)



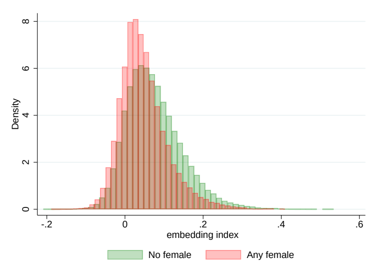
(d) Computers (24)



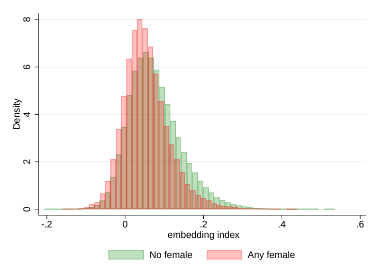
(e) Communications (26)



(f) Optical (28)



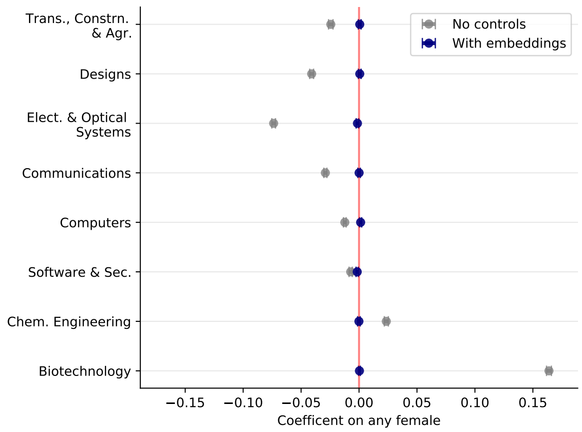
(g) Transportation (36)



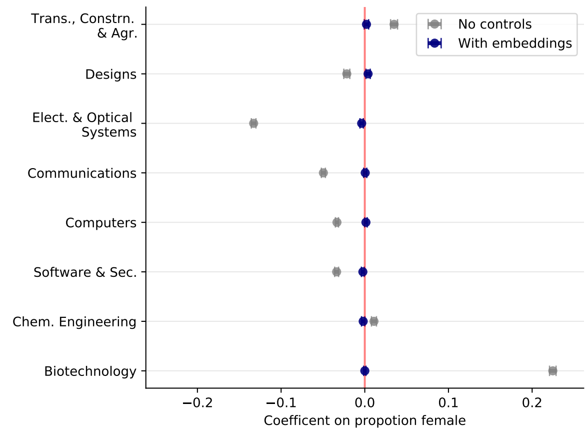
(h) Mech. Engineering (37)

Note: This Figure plots the distribution of the embedding index separately for patent applications written by mixed-gender patents by teams with no female inventors and by technology centers. To generate this Figure, I estimate an OLS regression, separately for every technology center, of the form $IA_i = \alpha + \beta F_i + C_i'\gamma + \epsilon_i$ where IA_i is an indicator for initial allowance, F_i is a mixed gender team indicator, and C_i are my preferred 2,046 text embeddings. The embedding index is the estimated linear combination $C_i'\hat{\gamma}$.

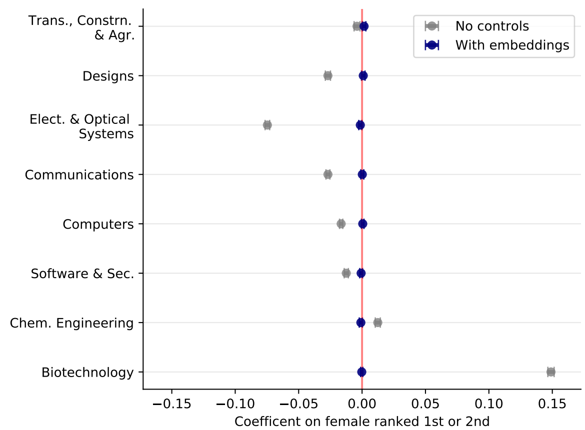
Figure 6: Balance test of technology centers



(a) Any female



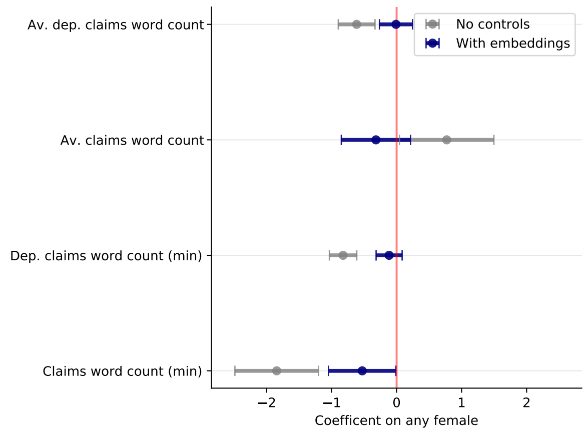
(b) Proportion female



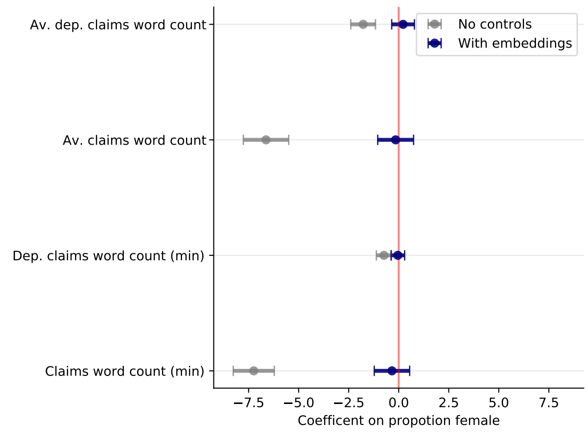
(c) Female 1st or 2nd

Note: This Figure plots the relationship between technology center indicators and the gender of the inventors' team with and without controlling for the patent application text embeddings. The gray dots are the estimates from an uncontrolled OLS regression, and the blue dots are the estimates from an OLS regression controlling linearly for the patent text embeddings. Bars indicate 95% confidence intervals based on robust standard errors.

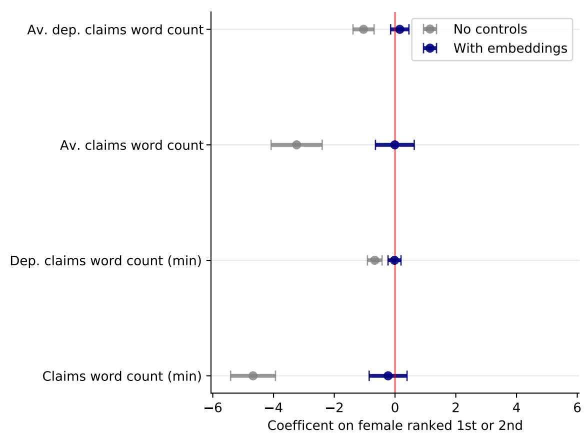
Figure 7: Balance test for claim statistics



(a) Any female



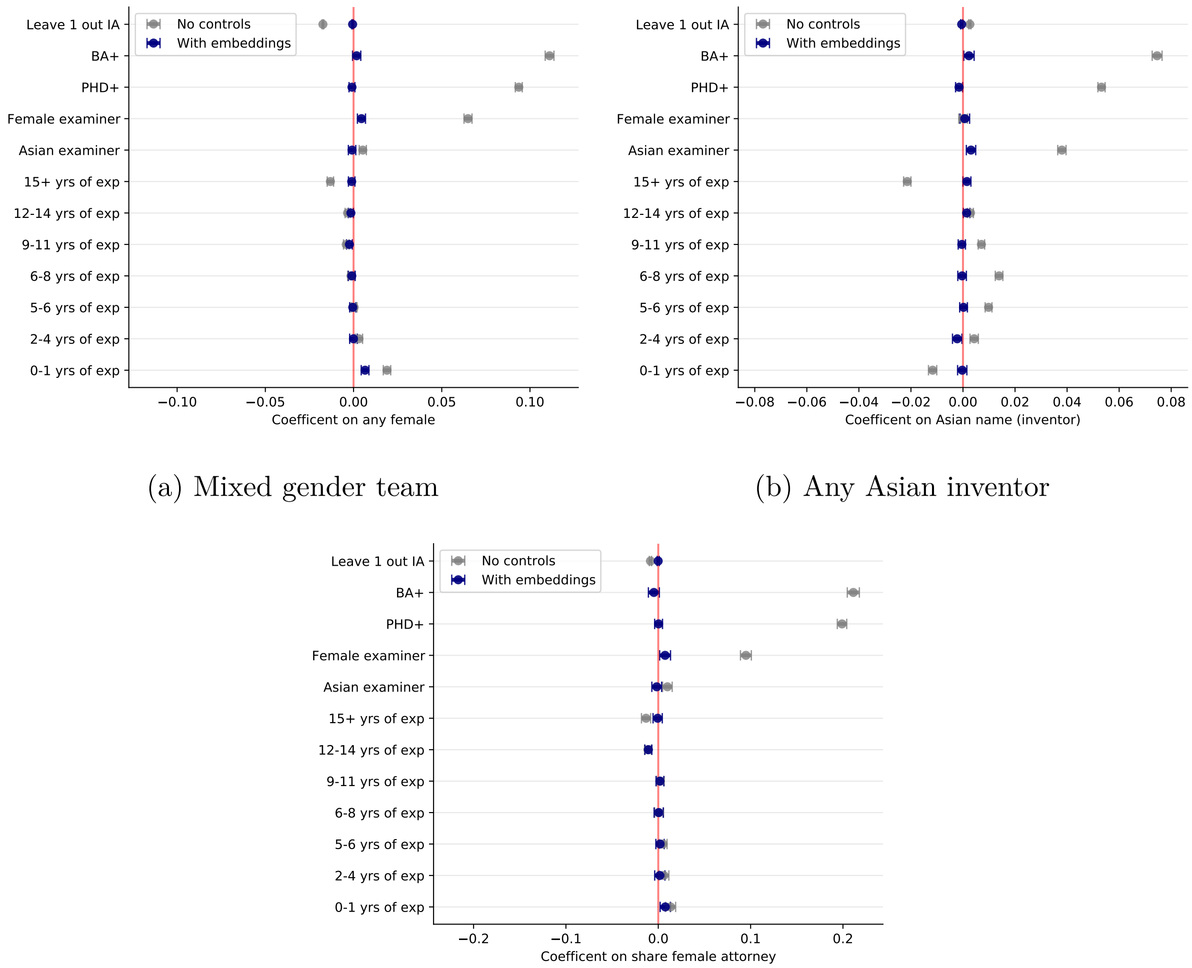
(b) Proportion female



(c) Female 1st or 2nd

Note: This Figure plots the relationship between patent application claim counts and the gender of the inventors' team with and without controlling for the patent application text embeddings. The gray dots are the estimates from an uncontrolled OLS regression, and the blue dots are the estimates from an OLS regression controlling linearly for the patent text embeddings. Bars indicate 95% confidence intervals based on robust standard errors.

Figure 8: Balance test of examiner characteristics



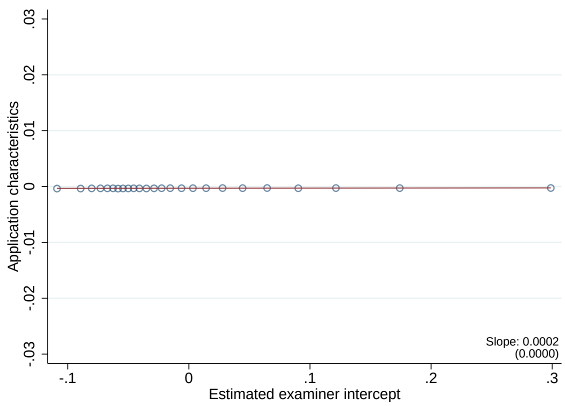
(a) Mixed gender team

(b) Any Asian inventor

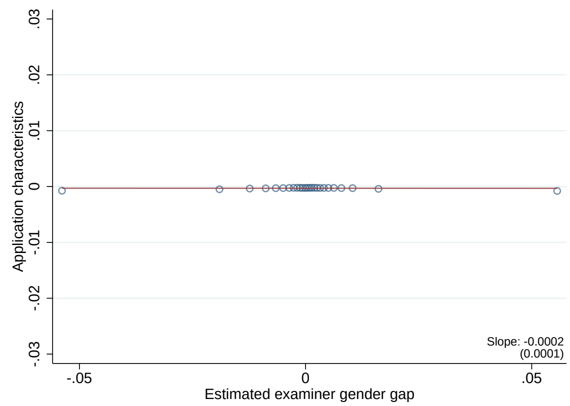
(c) Share female attorney

Note: This Figure plots the relationship between examiner characteristics and non-text characteristics of inventors and attorneys with and without controlling for the patent application text embeddings. The gray dots are the estimates from an uncontrolled OLS regression, and the blue dots are the estimates from an OLS regression controlling linearly for the patent text embeddings. Bars indicate 95% confidence intervals based on robust standard errors.

Figure 9: Omitted variable bias test in examiner leniency and gender bias



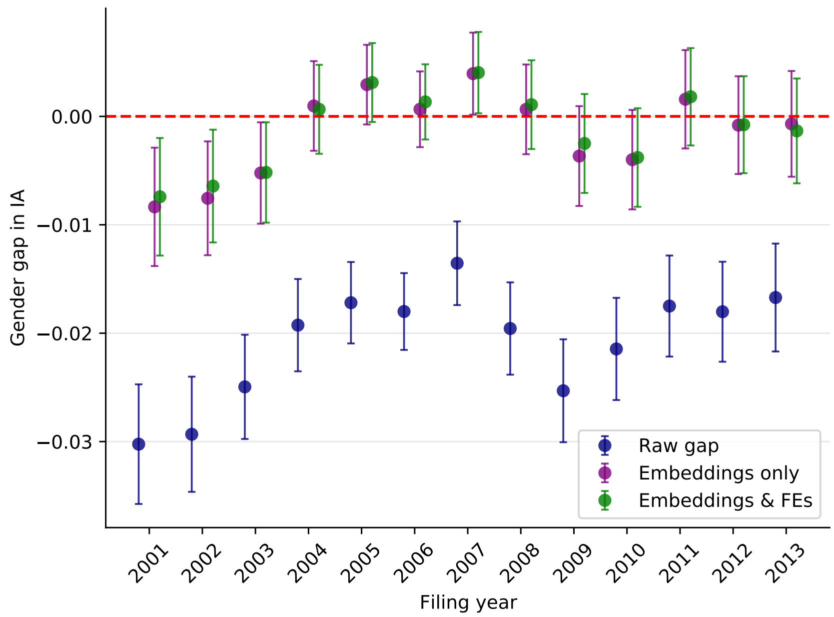
(a) Relationship w/ α_j



(b) Relationship w/ β_j

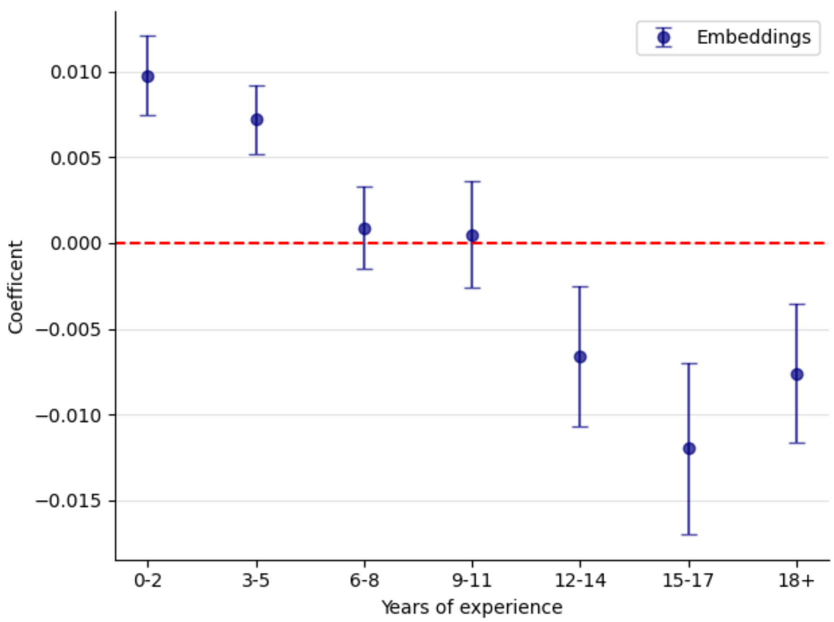
Note: This Figure plots the test for whether the estimated examiner leniency and gender bias effects ($\hat{\alpha}_j$ and $\hat{\beta}_j$ from equation 6) are correlated with other non-text characteristics that predict initial allowance: law firm experience, team size, an indicator for foreign priority, indicator for at least one Asian inventor, and proportion female attorney. The flat slopes indicate that examiner effects are not affected by the inclusion of these covariates.

Figure 10: Gender Gap in initial allowance by filing Year



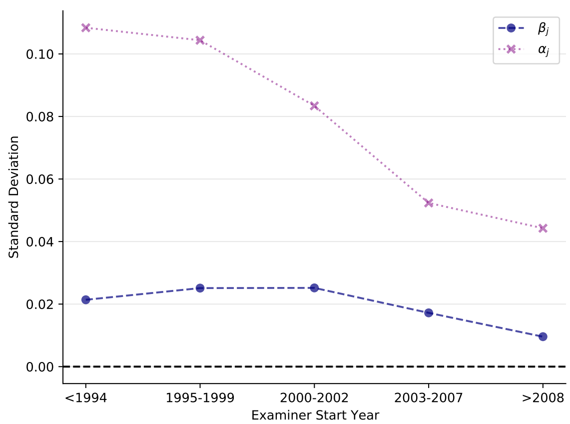
Note: This Figure plots the estimated gender gap and 95% confidence intervals in the initial allowance of patent applications filed between the years 2001 and 2013 by filing year. Blue dots plot the uncontrolled gender gap, purple dots plot the gender gap conditional on the text embeddings, and green dots plot the gender gap conditional on both text embeddings and art-unit-year and class fixed effects. Confidence intervals based on robust standard errors.

Figure 11: Gender gap by examiners' years of experience

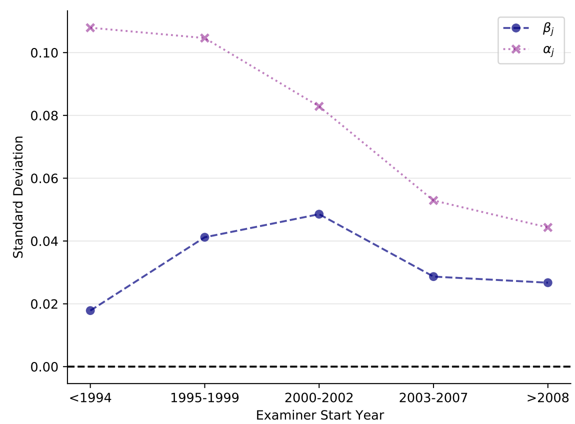


Note: This Figure plots the estimated gender gap and 95% confidence intervals in the initial allowance of patent applications filed between 2001 and 2013 by examiners' years of experience. The dots plot the gender gap conditional on the patent text embeddings. Confidence intervals based on robust standard errors.

Figure 12: Standard deviation of examiner gender gap and leniency by examiner start year



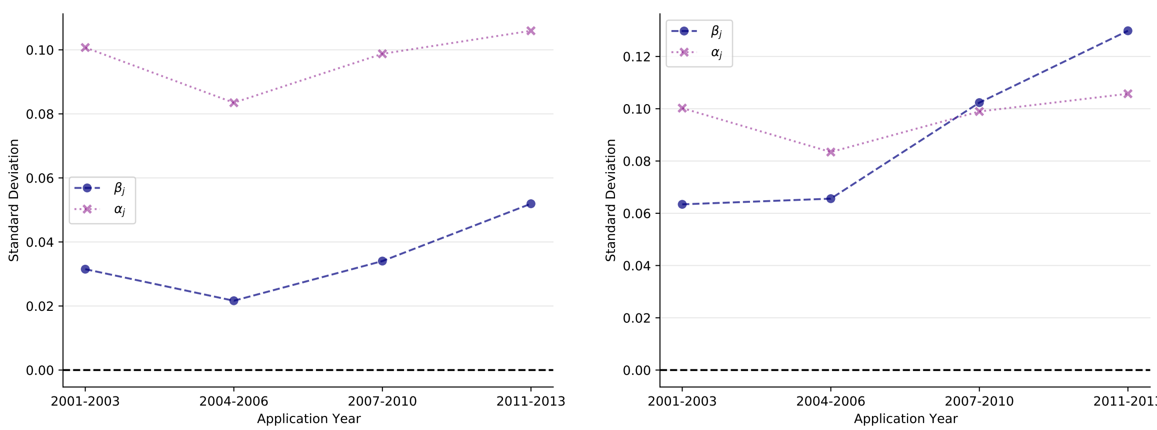
(a) Any female inventor



(b) Proportion female

Note: This Figure plots the bias-corrected standard deviation of examiner bias and leniency. The variance component is estimated in a linear regression with examiner fixed effects and examiner times application gender fixed effects separately by bins of examiner start year. The blue dots are the estimated standard deviation of examiners' gender gap, and the pink "X"s are the estimated standard deviations of examiners' leniency. All variance estimates are weighted by the number of applications per examiner.

Figure 13: Standard deviation of gender gap and leniency over time



(a) Any female inventor

(b) Proportion female

Note: This Figure plots the bias-corrected standard deviation of examiner bias and leniency. The variance component is estimated in a linear regression with examiner fixed effects and examiner times application gender fixed effects separately by bins of patent application filing year. The blue dots are the estimated standard deviation of examiners' gender gap, and the pink "X"s are the estimated standard deviations of examiners' leniency. All variance estimates are weighted by the number of applications per examiner.

Tables

Table 1: Patent applications' descriptive statistics

	Full sample	All male or unk	At least 1 female	Female ranked 1st or 2nd
	(1)	(2)	(3)	(4)
# of observations	1,224,315	1,019,495	204,820	143,118
Team size	2.477	2.257	3.573	2.948
Proportion female	0.075	0.000	0.450	0.536
Sole inventor	0.351	0.395	0.131	0.188
Sole female inventor	0.022	0.000	0.131	0.188
Initial allowance (IA)	0.083	0.086	0.067	0.065
Ever granted	0.646	0.656	0.595	0.571

Note: This table presents the descriptive statistics of the US patent applications filed between the years 2001-2013. Column 1 presents the counts and means of the full sample, column 2 of the no female applications, column 3 of the set of patent applications with at least one female author, and column 4 for the set of patent applications with at least one female ranked first or second in the application list of inventors.

Table 2: Examiners' descriptive statistics

		By examiner gender		
	All	Female	Male	Unknown
	(1)	(2)	(3)	(4)
# of examiners	8550	2055	5128	1367
Initial allowance rates	0.067	0.053	0.072	0.068
By start-year				
<1995	0.203	0.200	0.211	0.176
1996-2001	0.314	0.330	0.304	0.326
>2001	0.483	0.470	0.485	0.498

Note: This table presents the descriptive statistics of the 8,550 examiners in my sample, stratified by gender and years of experience.

Table 3: OLS estimates of the overall mean gender gap in initial allowance

	(1) IA	(2) IA	(3) IA	(4) IA
(i) Any female	-0.0200	-0.0035	-0.0010	-0.0007
	(0.0006)	(0.0006)	(0.0007)	(0.0006)
Adj. R^2	0.0007	0.0687	0.0682	0.1038
(ii) Proportion female	-0.0407	-0.0088	-0.0013	-0.0006
	(0.0011)	(0.0011)	(0.0012)	(0.0011)
Adj. R^2	0.0008	0.0687	0.0682	0.1038
(iii) Female 1st or 2nd	-0.0222	-0.0042	-0.0008	-0.0004
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Adj. R^2	0.0006	0.0687	0.0682	0.1038
Art-unit-year class FE	No	Yes	No	Yes
Embeddings	No	No	Yes	Yes
# of applications	1,220,512	1,220,393	1,220,512	1,220,393
# of examiners	8,519	8,519	8,519	8,519

Note: This table reports the OLS coefficients and adjusted R^2 from regressions of an indicator for initial allowance on the gender of the inventors' team. The gender of the inventors is represented by an indicator for having at least one female inventor (panel (i)), proportion female (panel (ii)), and an indicator for having female ranked first or second in the application list of inventors (panel (iii)). Robust standard errors are reported in parentheses.

Table 4: Oaxaca-Blinder and Inverse Probability reweighting estimates for the mean gender gap in initial allowances

	Oaxaca-Blinder	IPW		DML
	ATT	ATE	ATT	NN
	(1)	(2)	(3)	(4)
Any female	-0.0019	-0.0015	-0.0006	0.0006
	(0.0013)	(0.0009)	(0.0006)	(0.0007)

Note: This table reports matching estimates of the overall gender gap in initial allowance between mixed-gender teams and no female teams conditional on BERT embeddings. Column 1 reports the fully interacted (Oaxaca, 1973; Blinder, 1973) ATT estimate by running an OLS regression of initial allowance on embeddings only in the no-female sample and reporting the difference between the mean initial allowance rates of men and the fitted values on the no female regression on the mean embeddings among mixed-gender patents. Columns 2-3 report the Inverse Probability Weighting (IPW) estimates of the ATE and the ATT, estimating the propensity score with a logit regression. Column (4) reports the Doubly Robust Machine Learning (DML) (Chernozhukov et al., 2018) partially linear regression implemented using the Python package DOUBLEML. The model predicts initial allowance and gender with a neural network (NN) model, where the network's number of layers, nodes in each layer, and regularization parameters were chosen by cross-validation. Robust standard errors are reported in parentheses.

Table 5: Heterogeneity in gender bias in initial allowances

	(1) Any Female	(2) Proportion Female	(3) Female 1st or 2nd
(i) By examiner			
$Std(\alpha_j)$	0.090	0.090	0.090
$Std(\beta_j)$	0.024	0.037	0.022
$Corr(\alpha_j, \beta_j)$	-0.649	-0.840	-0.714
$\bar{\beta_j}$	-0.0009	-0.0014	-0.0009
# of examiners	8335	8335	8147
# of obs	1216346	1216346	1207069
(ii) By start-year			
$Std(\alpha_j)$	0.038	0.038	0.038
$Std(\beta_j)$	0.012	0.020	0.012
$Corr(\alpha_j, \beta_j)$	-0.802	-0.774	-0.764
$\bar{\beta_j}$	-0.0011	-0.0008	-0.0009
# of cohorts	38	38	38
# of obs	1216346	1216346	1216346
(iii) By art-unit			
$Std(\alpha_j)$	0.052	0.052	0.052
$Std(\beta_j)$	0.012	0.020	0.010
$Corr(\alpha_j, \beta_j)$	-0.333	-0.407	-0.405
$\bar{\beta_j}$	-0.0013	-0.0025	-0.0016
# of art-units	587	587	585
# of obs	1216329	1216329	1216278

Note: This table presents the bias-corrected standard deviation and correlations of examiners, examiner start-year, and art units leniency and gender bias, estimated in a linear regression controlling linearly for patent text embeddings. Different columns use different measures of the femaleness of the application. Column (1) uses an indicator for mixed-gender patents, column (2) uses the proportion female, and column (3) uses an indicator for having a female ranked first or second in the list of inventors. All variance components are weighted by the number of patent applications.

Table 6: Heterogeneity in examiner, start-year, and art unit gender bias explained by examiner experience

	(1) Any Female	(2) Proportion Female	(3) Female 1st or 2nd
(i) Examiner gap			
$Std(\beta_j)$	0.023	0.036	0.022
$Std(\beta_{exp})$	0.002	0.006	.
$Corr(\beta_j, \beta_{exp})$	0.125	0.025	.
# of examiners	8335	8335	8147
# of obs	1216315	1216315	1207038
(ii) Start-year gap			
$Std(\beta_j)$	0.010	0.016	0.011
$Std(\beta_{exp})$	0.003	0.008	.
$Corr(\beta_j, \beta_{exp})$	0.550	0.298	.
# of start-years	38	38	38
# of obs	1216315	1216315	1216315
(iii) Art-unit gap			
$Std(\beta_j)$	0.012	0.020	0.010
$Std(\beta_{exp})$	0.009	0.015	0.008
$Corr(\beta_j, \beta_{exp})$	-0.046	-0.050	-0.043
# of art-units	587	587	585
# of obs	1216298	1216298	1216247

Note: This table presents the bias-corrected standard deviation and correlations of examiners, examiners' start-year, and art units gender bias, estimated in a linear regression controlling for patent text embeddings using both units fixed effect and examiners years of experience fixed effect as described in equation 7. Different columns use different measures of the femaleness of the application. Column (1) uses an indicator for mixed-gender patents, column (2) uses the proportion female, and column (3) uses an indicator for having a female ranked first or second in the list of inventors. All variance components are weighted by the number of patent applications. Dots indicate an estimated negative variance and, therefore, undefined standard deviation and correlation.

Table 7: Relationship between gender gap and examiner characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PhD+	0.0011***					0.0002	0.0000
	(0.0002)					(0.0002)	(0.0002)
Female		0.0010***				0.0004**	-0.0001
		(0.0001)				(0.0001)	(0.0001)
Asian name			-0.0000			-0.0004*	-0.0007***
			(0.0002)			(0.0002)	(0.0002)
Yrs of experience				-0.0004***		-0.0003***	-0.0003***
				(0.0000)		(0.0000)	(0.0000)
Sh. mixed gender apps					0.0068***	0.0044***	-0.0087***
in USPC class					(0.0006)	(0.0007)	(0.0014)
Art-unit FE	No	No	No	No	No	No	Yes
Applications	1218137	1218137	1218137	1218137	1218137	1218137	1218137
Examiners	8335	8335	8335	8335	8335	8335	8335

Note: This table presents the relationship between examiner-level gender bias in initial allowance $\hat{\beta}_j$ and examiner characteristics estimated with an OLS regression. Columns 1-6 include only the examiner characteristics listed in the table, and column 7 reports the coefficients from a regression that additionally controls for art unit fixed effects. Robust standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8: Within examiner gender variability in gender gap

	Examiner gender		
	Female	Male	Unknown
	(1)	(2)	(3)
(i) OLS gap			
w/o embeddings	-0.0129	-0.0221	-0.0229
	(0.0011)	(0.0009)	(0.0018)
w/ embeddings	0.0007	-0.0020	-0.0021
	(0.0011)	(0.0010)	(0.0018)
(ii) Examiners fixed-effects			
$Std(\alpha_j)$	0.070	0.094	0.097
$Std(\beta_j)$	0.013	0.026	0.025
$\bar{\beta}_j$	-0.000	-0.001	-0.001
# of examiners	1,995	5,001	1,339
# of apps	289,703	732,605	194,038
Mean IA	0.062	0.090	0.091
Share mixed teams	0.187	0.138	0.153

Note: This table presents the distribution of gender bias by gender of the examiner. Panel (i) reports the mean gender bias separately by examiner gender with and without controlling for the text embeddings. Panel (ii) reports the bias-corrected standard deviation of examiners' gender bias and leniency estimated in a linear regression controlling linearly for patent text embeddings. All variance components are weighted by the number of patent applications.

Table 9: Gender bias in initial allowance and the rejection reason

	Rejection type			
	Obviousness (103)	Novelty (102)	Eligibility (101)	Writing (112)
	(1)	(2)	(3)	(4)
(i) OLS gap				
w/o embeddings	0.001	-0.014	0.022	0.041
	(0.002)	(0.002)	(0.001)	(0.002)
w/ embeddings	0.002	0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
(ii) Examiner fixed-effects				
(a) Variability				
$Std(\beta_j)$	0.028	0.028	0.028	0.026
$Std(\beta_j^R)$	0.046	0.043	0.039	0.041
$Corr(\beta_j, \beta_j^R)$	-0.493	-0.326	-0.255	-0.530
$\bar{\beta_j}$	0.000	0.000	0.000	0.000
$\bar{\beta_j^R}$	0.003	0.001	-0.000	-0.003
(b) Implied OLS				
coefficient	-0.298	-0.211	-0.184	-0.345
Implied R^2	0.254	0.107	0.065	0.297
# of examiners	6,996	6,996	6,996	6,996
# of apps	504,884	504,884	504,884	504,884
Mean IA	0.098	0.098	0.098	0.098
Mean rejection outcome	0.694	0.519	0.145	0.354

Note: This table presents the mean gender overall bias and its variability across examiners in initial allowance and the grounds for rejections. Panel (i) presents the mean gender bias of rejection reasons estimated in an OLS regression with and without text embeddings, and panel (ii) presents the bias-corrected standard deviation of examiners' gender bias estimated in a stacked regression having both initial allowance and the rejection reasons as outcomes, as described in Appendix Section C. All the regressions include controls for the patent text embeddings. All variance components are weighted by the number of patent applications.

Table 10: Robustness to other non-text characteristics

	(1)	(2)	(3)	(4)
(i) OLS gap				
Any female	-0.0010	-0.0010	-0.0010	-0.0011
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Other effect		-0.0002	-0.0008	0.0056
		(0.0006)	(0.0006)	(0.0009)
# of applications	1,220,512	1,220,512	1,220,512	1,220,512
# of examiners	8,519	8,519	8,519	8,519
(ii) Fixed-effect regression				
Std. any female	0.023	0.022	0.022	0.023
Std. other effect		0.022	0.023	0.039
Correlation		0.024	0.008	0.031
# of applications		1,215,230	1,214,970	1,216,346
# of examiners		8,300	8,300	8,335
Characteristic	-	Any foreign	Asian name	Lawyer experience

Note: This table reports the robustness of the mean gender bias and its variability across examiners to the inclusion of other non-text characteristics. Panel (i) reports the coefficients on mixed-gender teams and the other characteristics estimated in an OLS regression controlling for text embeddings. Panel (ii) reports the bias-corrected standard deviation of the examiner gender gap and examiner level sensitivity to other characteristics estimated in a regression on initial allowance on examiner fixed effects, examiner time gender fixed effects, and examiner times other characteristic fixed effects. All the regressions include controls for the patent text embeddings. All variance components are weighted by the number of patent applications. The names of the other characteristics are displayed in the last row.

Table 11: Sample selection parameter estimates

	log(R)
	(1)
(i) IA	
μ_0	-1.749
	(0.010)
μ_1	-0.010
	(0.017)
(ii) Outcome	
ψ_0	1.275
	(0.067)
ψ_1	0.247
	(0.025)
(iii) Random effects	
σ_{τ_0}	0.650
	(0.003)
σ_{τ_1}	0.338
	(0.007)
$Corr(\tau_1, \tau_0)$	0.039
	(0.220)
(iv) Outcome-IA dist.	
ρ	0.105
	(0.041)
σ	1.484
	(0.007)
Likelihood	-122581.4
# of parameters	19
# of apps	472408
# of examiners	7550

Note: This table reports the estimated parameter from a selection model (Heckman, 1979) of the joint distribution of initial allowance and stock market return. μ_0 and $\sigma_{\lambda 0}$ determine the distribution of examiners' initial allowance decision for all male applications, and μ_1 and $\sigma_{\lambda 1}$ determine the distribution of examiners' initial allowance decision of mixed gender applications. ψ_0 describes the mean Kogan et al. (2017) stock market return of all male applications, and ψ_1 describes the difference between all male and mixed-gender patents. $Corr(\lambda_1, \lambda_0)$ describes the correlation between examiners allowance threshold of all male vs. mixed gender patents. Panel (iv) reports the parameters of the joint distribution of initial allowance and market return error terms. The model includes the first two demeaned UMAP components of the text embeddings and their interaction with gender as controls, allowing the random thresholds to vary by these dimensions. I assume that the random thresholds that vary with the UMAP embeddings of all male and mixed-gender applications are uncorrelated. Observations include only patents assigned to publicly traded firms, and the market return model is estimated for initially allowed patents. Robust standard errors are reported in parentheses.

Table 12: Counterfactuals under uniformly zero bias

	(1) Allowance given	(2) Allowance taken	(3) Difference	(4) Total market loss	(5)
				IA	Ever granted
(A) Uniform zero bias					
(i) Mixed-gender apps					
Av. market return	5.867	5.688	0.231	1.372	10.333
Share	0.0116	0.0117			
(ii) All-male apps					
Av. market return	4.572	4.529	0.047	0.299	2.250
Share	0.0022	0.0022			
(B) Zero discretion					
(i) Mixed-gender patents					
Av. market return	6.270	5.522	0.231	4.712	35.570
Share	0.0401	0.0400			
(ii) All male patents					
Av. market return	4.972	4.476	0.047	5.447	41.011
Share	0.0310	0.0303			

Note: This table reports the average market return (measured in a million US Dollars) of all-male and mixed-gender patent applications under the status-quo distribution of examiners' gender bias reported in Table 11 and two counterfactual exercises. Panel (A) reports the counterfactual of uniform zero bias while allowing for variation in discretion across examiners, and panel (B) reports the results with zero discretion, setting all examiners' threshold to the one that results with the mean initial allowance rate. Column (1) reports the average market return among the patent applications that were not allowed under the status quo but are allowed under the uniform zero bias/zero discretion simulation. Column (2) reports the average market return among the applications allowed under the status quo but not under the uniform zero bias/zero discretion simulation. Column (3) reports the difference between column (1) and column (2). Columns (4)-(5) report the total yearly difference in market return for 40,000 applications assigned to publicly traded firms, with 15% mixed-gender teams. Column (4) reports the total market return loss among initially allowed patent applications, and column (5) reports the total loss for ever-granted patent applications, assuming the first round of examination behavior and later rounds of examination distribute similarly.

A Appendix Figures and Tables

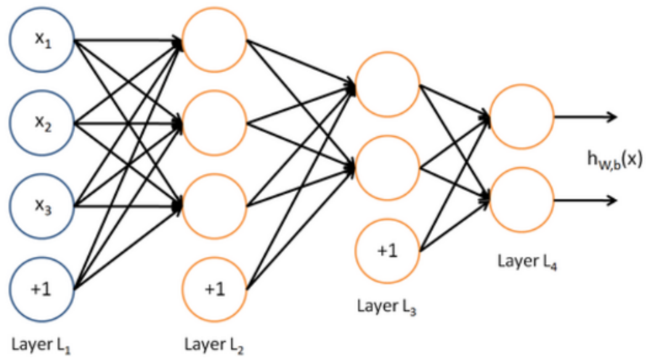
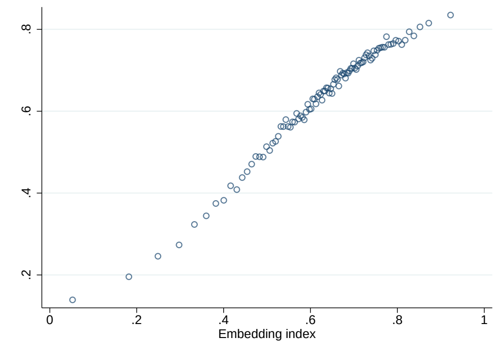


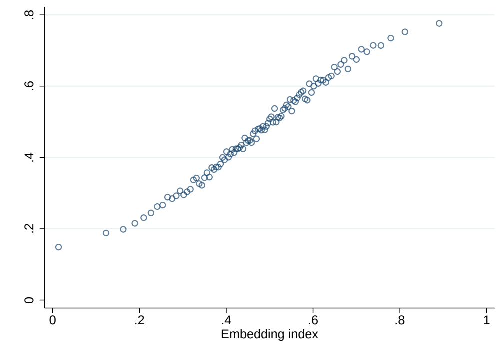
Figure A.1: Visual Illustration of a Neural Network Model

Note: This Figure illustrates an example of a generic neural network model with 3 hidden layers.

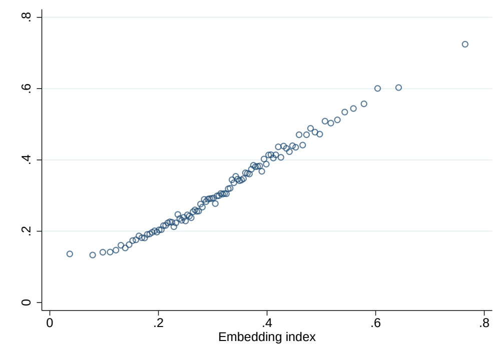
Figure A.2: Split sample binned scatter of embeddings prediction of patent quality proxies



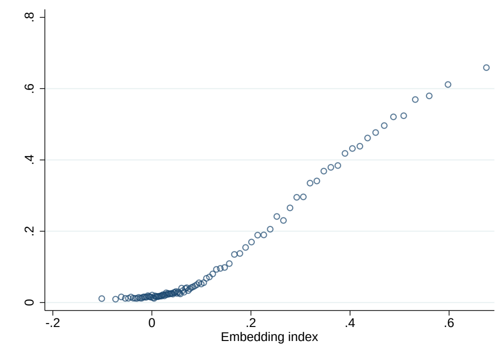
(a) Rejections - non-obviousness



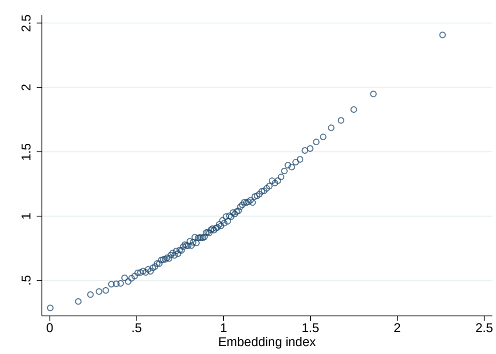
(b) Rejections - lack of novelty



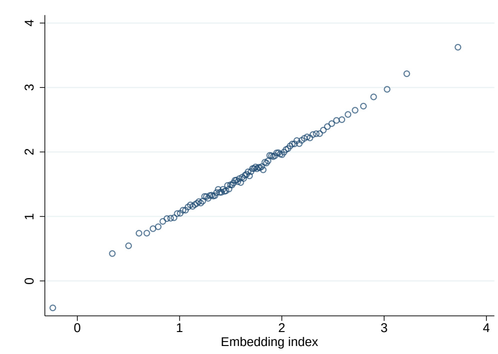
(c) Rejections - writing



(d) Rejections - eligibility



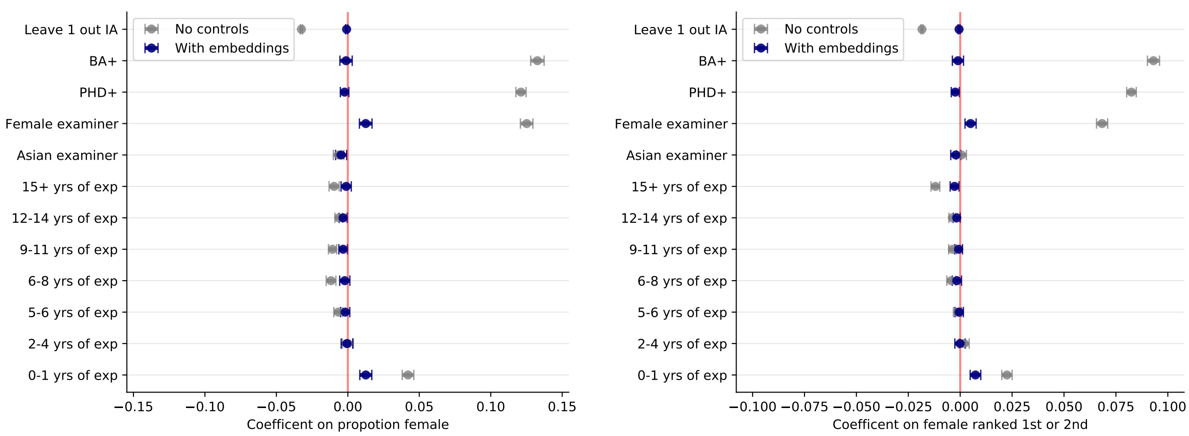
(e) Log citations



(f) Log market return

Note: This Figure plots a binned scatter with 100 bins of a split sample prediction of examiners' decisions, log citations, and log market return with the patent text embeddings. Subfigure (a) plots the prediction for rejection based on the ground of non-obviousness, subfigure (b) plots the prediction for rejection based on the ground of lack of novelty, subfigure (c) plots the prediction for rejection based on the ground of inadequate writing, subfigure (d) plots the prediction for rejection based on the ground of not following the eligibility criteria, panel (e) plots the prediction of the log number of citations after granting among granted patents, and subfigure (f) plots the prediction of Kogan et al. (2017)'s measure for patent market return.

Figure A.3: Balance test for examiner characteristics using alternative female definitions

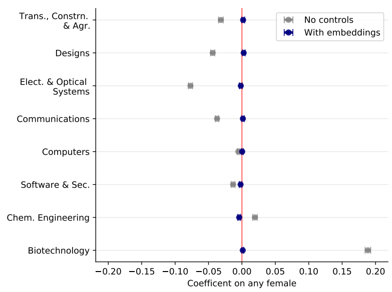


(a) Proportion female

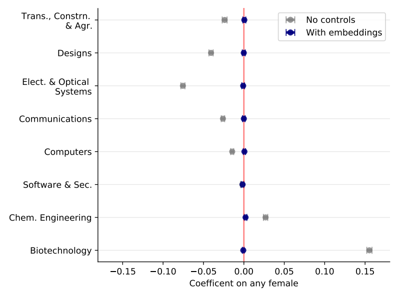
(b) Female 1st or 2nd

Note: This Figure plots the relationship between examiner characteristics with different measures of patent "femaleness" with and without controlling for the patent application text embeddings. The gray dots are the estimates from an uncontrolled OLS regression, and the blue dots are the estimates from an OLS regression controlling linearly for the patent text embeddings. Bars indicate 95% confidence intervals based on robust standard errors.

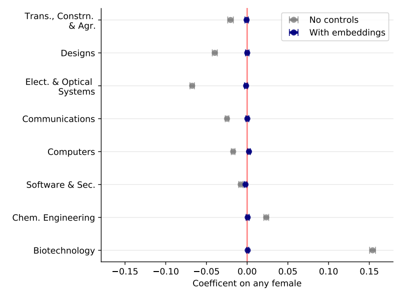
Figure A.4: Balance test by year



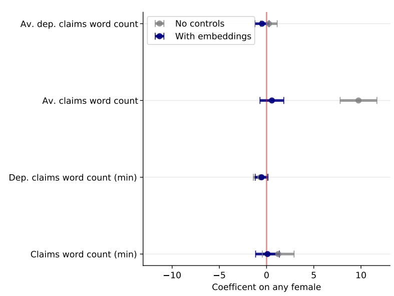
(a) 2001-2004



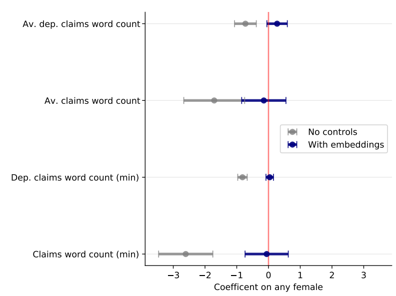
(b) 2005-2009



(c) 2010-2013

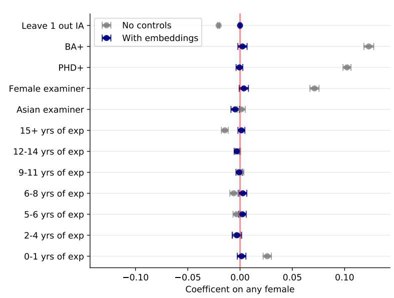


(d) 2001-2004

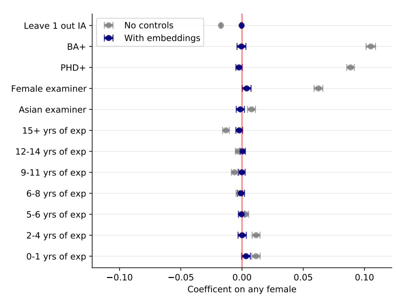


(e) 2005-2009

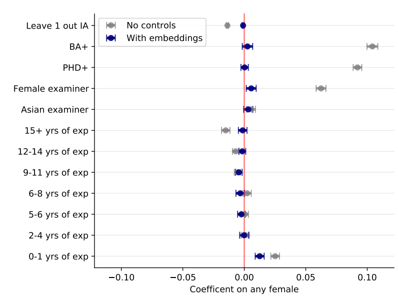
(f) 2010-2013



(g) 2001-2004



(h) 2005-2009



(i) 2010-2013

Note: This Figure plots the relationship between patent application and examiner characteristics and the gender of the inventors' team with and without controlling for the patent application text embeddings. The gray dots are the estimates from an uncontrolled OLS regression, and the blue dots are the estimates from an OLS regression controlling linearly for the patent text embeddings. Bars indicate 95% confidence intervals based on robust standard errors.

Table A.1: Adjusted R^2 on initial allowance and any female by embedding layer

			Adj. R^2		Partial R^2, art-unit-yr class		Partial R^2, examiner	
Claim layer	Description layer	# of embeddings	IA	Any female	IA	Any female	IA	Any female
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(0, 0, 0)	(1, 0, 0)	1023	0.0499	0.0975	0.0213	0.0377	0.0238	0.0381
(0, 0, 0)	(0, 0, 1)	1023	0.0499	0.0939	0.0222	0.0349	0.0250	0.0351
(0, 0, 0)	(0, 1, 0)	1023	0.0500	0.0961	0.0217	0.0365	0.0244	0.0368
(0, 0, 0)	(1, 1, 0)	2046	0.0535	0.1032	0.0248	0.0440	0.0276	0.0444
(0, 0, 0)	(0, 1, 1)	2046	0.0544	0.1016	0.0256	0.0426	0.0287	0.0429
(0, 0, 0)	(1, 1, 1)	3069	0.0566	0.1067	0.0280	0.0483	0.0311	0.0486
(1, 0, 0)	(0, 0, 0)	1023	0.0616	0.0908	0.0329	0.0312	0.0375	0.0315
(0, 1, 0)	(0, 0, 0)	1023	0.0626	0.0902	0.0342	0.0308	0.0390	0.0311
(0, 0, 1)	(0, 0, 0)	1023	0.0639	0.0893	0.0361	0.0302	0.0414	0.0304
(1, 1, 0)	(0, 0, 0)	2046	0.0668	0.0950	0.0382	0.0360	0.0434	0.0362
(1, 0, 0)	(1, 0, 0)	2046	0.0673	0.1014	0.0382	0.0425	0.0434	0.0428
(1, 0, 0)	(0, 1, 0)	2046	0.0675	0.1010	0.0383	0.0421	0.0436	0.0424
(1, 0, 0)	(0, 0, 1)	2046	0.0675	0.1005	0.0385	0.0417	0.0439	0.0420
(0, 1, 0)	(0, 1, 0)	2046	0.0682	0.1005	0.0393	0.0417	0.0448	0.0420
(0, 1, 0)	(1, 0, 0)	2046	0.0684	0.1015	0.0393	0.0426	0.0448	0.0429
(0, 1, 1)	(0, 0, 0)	2046	0.0684	0.0947	0.0399	0.0358	0.0454	0.0361
(0, 0, 1)	(0, 0, 1)	2046	0.0693	0.0991	0.0411	0.0407	0.0470	0.0409
(1, 0, 0)	(1, 1, 0)	3069	0.0696	0.1060	0.0407	0.0479	0.0461	0.0482
(1, 0, 0)	(0, 1, 1)	3069	0.0702	0.1051	0.0412	0.0470	0.0466	0.0473
(0, 1, 0)	(1, 1, 0)	3069	0.0706	0.1060	0.0418	0.0479	0.0473	0.0482
(0, 1, 0)	(0, 1, 1)	3069	0.0710	0.1047	0.0422	0.0467	0.0479	0.0470
(1, 1, 0)	(1, 0, 0)	3069	0.0716	0.1044	0.0427	0.0462	0.0484	0.0465
(1, 1, 0)	(0, 1, 0)	3069	0.0717	0.1040	0.0428	0.0458	0.0485	0.0461
(1, 1, 0)	(0, 0, 1)	3069	0.0718	0.1036	0.0430	0.0455	0.0488	0.0458
(0, 0, 1)	(1, 1, 0)	3069	0.0722	0.1061	0.0435	0.0480	0.0493	0.0483
(0, 0, 1)	(0, 1, 1)	3069	0.0725	0.1046	0.0438	0.0466	0.0498	0.0469
(0, 1, 1)	(0, 1, 0)	3069	0.0730	0.1037	0.0443	0.0456	0.0503	0.0459
(0, 1, 1)	(1, 0, 0)	3069	0.0731	0.1046	0.0443	0.0464	0.0502	0.0467
(0, 1, 1)	(0, 0, 1)	3069	0.0731	0.1032	0.0446	0.0452	0.0506	0.0455
(1, 1, 0)	(1, 1, 0)	4092	0.0732	0.1080	0.0448	0.0507	0.0505	0.0510
(1, 1, 0)	(1, 0, 1)	4092	0.0736	0.1079	0.0452	0.0506	0.0510	0.0509
(1, 0, 1)	(1, 1, 0)	4092	0.0745	0.1082	0.0462	0.0509	0.0522	0.0512
(1, 0, 1)	(1, 0, 1)	4092	0.0746	0.1077	0.0463	0.0504	0.0524	0.0507
(0, 1, 1)	(0, 1, 1)	4092	0.0748	0.1070	0.0466	0.0498	0.0527	0.0501
(0, 1, 1)	(1, 0, 1)	4092	0.0749	0.1080	0.0466	0.0507	0.0527	0.0510
(1, 0, 1)	(0, 1, 1)	4092	0.0749	0.1073	0.0465	0.0500	0.0526	0.0503
(1, 1, 1)	(1, 1, 1)	6138	0.0779	0.1123	0.0506	0.0567	0.0568	0.0570

Note: This table presents the adjusted R^2 and the partial adjusted R^2 from running regressions of initial allowance and a mixed gender indicator on different layers of text embeddings. Column 1 displays the claims text embeddings layer, column 2 presents the description text embeddings layer, and column 3 displays the total number of embeddings in the estimated regression, where each embedding layer includes 1023 features.

Table A.2: Relationship between omitted covariates and initial allowance

	(1)
	IA
Female attorney	-0.0018
	(0.0008)
Asian attorney	-0.0009
	(0.0005)
Attorney experience	0.0028
	(0.0006)
Team size	-0.0008
	(0.0002)
foreign_p	0.0015
	(0.0012)
# of applications	1220508

Note: This table reports the relationship between omitted covariation and initial allowance when estimating the examiner-level gender bias conditional of text embeddings. The table presents the coefficients on female patent attorney gender, Asian attorney, number of previously granted patents, inventors' team size, and indicator for foreign priority. The model includes a fixed effect for every examiner, and a fixed effect for every examiner times an indicator for having at least one female in the inventors' team. Robust standard errors are reported in parentheses.

Table A.3: Gender bias in initial allowance for single gender teams

	IA (1)	IA (2)	IA (3)	IA (4)
(i) All female vs no female	-0.0364	-0.0112	-0.0010	-0.0002
	(0.0013)	(0.0014)	(0.0014)	(0.0014)
Adj. R^2	0.0004	0.0688	0.0693	0.1050
# of applications	1,062,510	1,062,369	1,062,510	1,062,369
# of examiners	8,519	8,519	8,519	8,519
(ii) Sole inventor	-0.0345	-0.0109	-0.0013	-0.0006
	(0.0015)	(0.0015)	(0.0016)	(0.0016)
Adj. R^2	0.0008	0.0691	0.0743	0.1085
# of applications	428,330	428,040	428,330	428,040
# of examiners	8,516	8,516	8,516	8,516
Art-unit-year class FE	No	Yes	No	Yes
Embeddings	No	No	Yes	Yes

Note: This table reports the OLS coefficients from regressions of an indicator for initial allowance on the gender of the team of inventors, using subsamples with single-gender teams. Panel (i) reports the estimates from the subsample of patent applications with all female inventors teams vs. no female inventors, and panel (ii) reports the subsample of sole inventors. Robust standard errors are reported in parentheses.

Table A.4: Variance components using inverse probability weighting

	(1) KSS	(2) IPW
$Std(\alpha_j)$	0.090	0.0930
$Std(\beta_j)$	0.024	0.0174
$\bar{\beta}_j$	-0.001	-0.0051
# of examiners	8335	7550
# of applications	1,216,346	1,220,195

Note: This table reports the variance components of examiners leniency (α_j) and examiners gender bias (β_j). Column (1) reports the variance components from Table 5 by estimating a linear model with examiners and examiners times gender fixed effect controlling for embeddings linearly. Column (2) reports the variance component by first estimating the propensity score of each examiner and application gender only among examiners with at least 100 applications. And then estimating the variance component using the leave-one-out formula, reweighting the observation using the propensity score.

Table A.5: Within examiner variance in gender bias, proportion female

	Female (1)	Male (2)	Unknown (3)
(i) OLS gap			
w/o emmbeddings	-0.0288	-0.0439	-0.0459
	(0.0018)	(0.0017)	(0.0033)
w/ emmbeddings	0.0001	-0.0021	-0.0008
	(0.0019)	(0.0017)	(0.0033)
(ii) Fixed-effect regression			
$Std(\alpha_j)$	0.071	0.094	0.097
$Std(\beta_j)$	.	0.032	0.073
$\bar{\beta}_j$	-0.001	-0.002	-0.000
# of examiners	1,995	5,001	1,339
# of apps	289,703	732,605	194,038
Mean IA	0.062	0.090	0.091
Share mixed teams	0.087	0.061	0.065

Note: This table presents the distribution of gender bias by the gender of the examiner using the proportion of females in the team of inventors as a measure for the "femaleness" of the patent application. Panel (i) presents the mean gender gap separately by examiner gender with and without controlling for the text embeddings. Panel (ii) presents the Kline et al. (2020) bias-corrected variance components of the gender bias and leniency estimated in a linear regression controlling for patent text embeddings. All variance components are weighted by the number of patent applications.

Table A.6: Within examiner gender variance in gender bias, female ranked first or second

	Female (1)	Male (2)	Unknown (3)
OLS gap			
w/o emmbeddings	-0.0163	-0.0238	-0.0253
	(0.0012)	(0.0011)	(0.0020)
w/ emmbeddings	-0.0003	-0.0012	-0.0016
	(0.0013)	(0.0011)	(0.0020)
Fixed-effect regression			
$Std(\alpha_j)$	0.070	0.094	0.097
$Std(\beta_j)$	0.013	0.025	0.017
$\bar{\beta}_j$	-0.002	-0.001	0.000
# of examiners	1,953	4,875	1,319
# of apps	288,120	726,023	192,926
Mean IA	0.062	0.090	0.091
Share mixed teams	0.133	0.096	0.104

Note: This table presents the distribution of gender bias by the gender of the examiner using an indicator for having at least one female ranked first or second in the inventors' team as a measure for the "femaleness" of the patent application. Panel (i) presents the mean gender gap separately by examiners' gender with and without controlling for the text embeddings. Panel (ii) presents the Kline et al. (2020) bias-corrected variance components of examiners' gender bias and leniency estimated in a linear regression controlling for patent text embeddings. All variance components are weighted by the number of patent applications.

B Data Appendix

B.1 Patent Data

The main data source is the USPTO Patent Examination Research Dataset (Graham et al., 2015) which includes the universe of all public patent applications available online in the Public Patent Application Information Retrieval system (Public PAIR).[26] For every patent application, the Public PAIR data includes information on inventors' first and last name together with additional variables such as country, application number, publication number, the grant date if granted, and examiners, art-unit, and technological classes and sub-classes identifiers.

This dataset is merged to several other datasets:

1. The USPTO Patents View data.[27] It includes detailed information on both granted patents and patent applications. Specifically, this source includes the list of all the patents it cites, including granted and non-granted patents, and an implied identifier for inventors.

2. The Patent Claims Research Dataset (Marco et al., 2019).[28] This data-set includes detailed information on the number of claims and change in claims of patent applications and granted patent.

3. "Google Patents Research Data" from which I merged the abstract and description of each patent application.

4. Examiners roster, pay scale, and education data. Frakes and Wasserman (2014) generously provided me with detailed roster data and pay scale dated from 1994 they received through FOIA requests. These data are used to determine the start year of examiners (see detail below) and their years of experience.

5. Kogan et al. (2017) patent market value data. They provide estimates of the market

[26]The data can be found here: https://www.uspto.gov/learning-and-resources/electronic-data-products/patent-examination-research-dataset-public-pair

[27]https://www.patentsview.org/download/

[28]https://www.uspto.gov/learning-and-resources/electronic-data-products/patent-claims-research-dataset

value using a series of event study designs of the stock market return of patents among publicly traded patents.

6. Patent Maintenance Fee Events.[29] This dataset records all the maintenance fee events for granted patents granted from September 1, 1981. These fees are due 4, 8, and 12 years after the patent grant and are increasing over time.

7. USPTO Office Action Rejection.[30] 'Office action" is a written notification to the applicant of the examiner's decision on patentability. It generally discloses the reasons for any rejections, objections, or requirements and includes relevant information or references that the applicant may find useful for responding to the examiner and deciding whether to continue prosecuting the application. This data set includes all the mailed office actions from 2008 to 2017. It includes information on the grounds for rejections raised.

Sample restriction: I restrict the sample to utility[31] patent applications filed after November 29th, 2000[32] and before January 1st, 2014. To avoid detecting differential behavior to non-US inventors, and since the gender identification relies on the gender distributions of first names provided by the US Social Security Administration, I include only patent applications written by US inventors in my analysis.

B.2 Variable Construction

B.2.1 Inventors' name coding

The application data includes for every patent application the first name, middle name, and last name of each inventor. To assign gender and an indicator for a foreign name I follow the following procedure. For every first name, I assign a probability of being a woman based on the gender name distribution provided by the US Security Administration (SSA).[33] In

[29] https://www.uspto.gov/learning-and-resources/electronic-data-products/additional-patent-data-products

[30] https://developer.uspto.gov/product/patent-application-office-actions-data-stata-dta-and-ms-excel-c

[31] Utility patents are granted for the "invention of a new and useful process, machine, manufacture, or composition of matter" (USPTO 2010).

[32] Since the American Inventors Protection Act of 1999 almost all the USPTO patent applications filed after 29 November 2000 were published online, regardless of whether they are granted or not.

[33] https://www.ssa.gov/oact/babynames/limits.html

cases where the first name is missing or includes only the first letter, I assign gender to the middle name.[34] Applications with at least one inventor with missing first and middle names are excluded from the analysis.

I classify a name as male if the threshold probability for male names in the SSA data is higher than 90%. Since women make up roughly 11% of the inventors and men account for 80%,[35] I set the women threshold to be higher, at 98.5%, roughly equating the type one error across gender, assuming the distribution of names in the general population is the same in the inventor population. Using this protocol I could assign gender to 75% of the names in my final sample.

B.2.2 Examiner Gender Coding

Unlike with inventors' gender coding, my goal was to assign gender to all possible examiners. Therefore I use a collection of data sources by assigning gender to each name in the following order:

I assign gender to examiners using the following data sources by order in which they are used:

1. The US SSA administrative baby names by gender.
2. Name gender published by the United Kingdom Intellectual Property Organization. This dataset is binary, a name is classified as either male or female.
3. WIPO Dataset.[36] Name gender dataset published by World Intellectual Property Organization. Its main advantage is that it includes names of different languages across countries.
4. gender-guesser Python package.
5. After exhausting all the datasets mentioned before, I use https://genderize.io/Genderize.io for the detection of non-East-Asian names because they are known to not be accurate

[34] Although the middle name could potentially be of a gender different from the first-name, I assume that from the perspective of the examiners, this is the name that embodies the gender signal.

[35] Lissoni et al. (2018) find that in 2016 women account for 12% of the inventors. Following their analysis and using their data that identified the gender of inventors of granted patents using by country name distribution, I find that in the time period of this study, women account for 11% of the inventors.

[36] https://www.wipo.int/publications/en/details.jsp?id=4125

for Asian names.[37]

As a result, I could identify 80% of the examiners in my data set.

B.2.3 Ethnicity

To identify the ethnicity of examiners and inventors I apply the raceBERT algorithm (Parasurama, 2021) that was trained on the U.S. Florida voter registration data set using a BERT architecture. The model predicts the likelihood of a name belonging to 5 U.S. census race categories (White, Black, Hispanic, Asian & Pacific Islander, American Indian & Alaskan Native). Using this algorithm I classify an Asian name as either East Asian or Japanese. Using this algorithm I find that 46% of the unique inventor names in my data are Asians.

B.2.4 Examiners' Start Year and Years of Experience

To calculate the years of experience of each examiner and start year I use two sources of information. First, I use the roster data from Frakes and Wasserman (2014), which includes the years 1992-2014. My sample starts before 1992, so I fill in the missing information by identifying the first office action by examiners using the transaction data set provided in the public PAIR data-set. Specifically, any examiner application transactions with "DOCK" record indicates an assignment or a change in assignment of an application's examiner, therefore for every application, I use the date of the most recent "DOCK" record to indicate the date on which the application is docketed to the current examiner.

There is a concern that the start year classification using the transaction data is downward biased as the examiner records in the Public PAIR data set assign the application's examiner as the one who was assigned to process or archive the application at the time of disposal. In an effort to account for that, I modify the start year of examiners that have suspiciously long "gap years", meaning they have no assigned patents after the start years. I do so by defining the start year only if the examiner doesn't have a gap size of a certain size. I find the optimal gap size by minimizing the distance between the start year from the administrative FOIA records and the implied start year for examiners whose start year is greater than 1994 and apply this rule to the examiners with missing information.

[37] For more details see https://jmla.pitt.edu/ojs/jmla/article/view/1289

B.2.5 Attorneys

The Public PAIR data set has a table named "attorney_agent" which records the first name, last name, and practice category of patent attorney(s) in each application. Interestingly, the filing of patent applications seems to have a large number of attorneys/agents involved where the average number of attorneys/agents is 28.20.

C Leave out Estimation of the Variance Component

I estimate the following OLS regression:

$$y_i = \alpha_{J(i)} + \beta_{J(i)} F_i + x_i' \gamma + \epsilon_i$$

where y_i is the outcome of interest, usually an indicator for initial allowance, F_i indicates the femaleness of the patent application, usually an indicator for a mixed gender patent, α_j are examiner fixed effects, β_j is the examiner level tendency to overvalue patent written by female inventors, and x_i is a vector of over 2,000 continuous embeddings. This specification can be written as:

$$y_i = X_i' \eta + \epsilon_i$$

where X_i collects the vectors of examiner indicators, examiner times gender indicators, and the embedding features. Using that matrix representation, any variance component can be written in a quadratic form:

$$\sigma^2 = \delta' A \delta$$

where $\delta = (\alpha', \beta')'$ are the collected $\alpha = (\alpha_1, .., \alpha_J)'$, and $\beta = (\beta_1, .., \beta_J)'$ examiner level coefficients, and A is the relevant weighting matrix. Kline et al. (2020) suggest estimating:

$$\hat{\sigma^2} = \hat{\delta}' A \hat{\delta} - \sum_{i=1}^{n} B_{ii} \hat{\xi}_i^2$$

where $B_{ii} = X_i' S_{ii}^{-1} A S_{ii}^{-1} X_i$ measures the influence of the i's squared error ϵ_i^2, $S_{ii} = \sum_i X_i X_i'$, $\xi_i^2 = \mathbb{V}(\epsilon_i | X_i)$ is the variance of the i's error, $\hat{\xi}_i^2 = \frac{y_i(y_i - X_i'\eta)}{1 - P_{ii}}$ is a the leave-i-out estimator described in Kline et al. (2020), and $P_{ii} = X_i' S_{ii}^{-1} X_i$ is the leverage of the i's observation on the estimate of $\hat{\eta}$. Kline et al. (2020) provide the conditions on the X_i matrix that ensure consistency of the bias corrected estimator.

Computation of $\hat{\sigma^2}$ is intensive as it requires computing the B_{ii} and P_{ii} from a model with over 18 thousand parameters. Therefore, as suggested in Kline et al. (2020) I exploit the random projection method by Lindenstrauss (1984) when approximating $\hat{\sigma^2}$. The Matlab code provided by Kline et al. (2020) relies on MATLAB's preconditioned conjugate gradient routine *pcg* which solves systems of linear equations in large sparse problems. However, in my settings, X_i includes a dense embedding component preventing the algorithm from converging. To accommodate this problem I orthogonalize the embeddings component matrix $E_i = QR$ using QR decomposition so $Q_i'Q_i$ equals to identity matrix that can be represented as a sparse matrix and enables convergence of the *pcg* function.

C.1 Covariance Across Different Regressions

In Section 9.1 I estimate the following model:

$$IA_i = \alpha_{j(i)} + \beta_{j(i)}F_i + x_i'\gamma + \epsilon_i$$
$$IR_i = \alpha^R_{j(i)} + \beta^R_{j(i)}F_i + x_i'\gamma^R + \epsilon^R_i$$

where IA_i is an indicator for initial allowance and IR_i is an indicator for the rejection reason in the first round of examination. The variance component of interest is $cov(\beta_{j(i)}, \beta^R_{j(i)})$, the covariance between the gender gap in initial allowance and the gender gap in that particular rejection reason. Writing this model in a matrix representation:

$$IA_i = X_i'\eta + \epsilon_i$$
$$IR_i = X_i'\eta^R + \epsilon^R_i$$

we can easily see that both of the regressions share the same design matrix X_i described above. As described in Lachowska et al. (2022) the estimator of the covariance using the leave-out procedure is therefore:

$$\widehat{cov(\beta_{j(i)}, \beta^R_{j(i)})} = \hat{\beta}'A\hat{\beta}^R - \sum_{i=1}^{n} B_{ii}\hat{\xi}^2_{i12}$$

where $\beta = (\beta_1, .., \beta_J)'$ are the collected examiner level gender bias in initial allowance and $\beta^R = (\beta^R_1, .., \beta^R_J)'$ are the collected examiner level gender bias R_i, A_i is the relevant weighting matrix, B_{ii} is identical to the one described in the previous section and $\hat{\xi}^2_{i12} = \frac{IR_i(IA_i - X_i\hat{\eta})}{1-P_{ii}}$ is the leave-i-out estimator of the covariance of the i's error in the two regression models.