A Multi-aspect Analysis of Gender Bias on Online Student Evaluations *

Sofia Maria Nikolakaki       Joseph Lai       Evimaria Terzi

Abstract

Institutions widely use student evaluations to assess the faculty’s teaching performance, but underlying trends and biases can influence their interpretation. Using data from Rate My Professors, we conduct the largest and most recent quantitative data analysis to study questions related to the evaluation criteria that students have when they review the performance of their male and female professors. Our analysis spans data from two decades (1999-2019), thus taking into account recent changes on the website and in the perception of students, and demonstrates interesting insights related to how students perceive the teaching style and personality traits of their male and female professors. We also present the first analysis that investigates how gender bias evolves over time and changes over space. We believe that our results are interesting from a sociological viewpoint, as they investigate the role of gender in higher education by disclosing how students perceive and evaluate professors of different genders. In addition, we believe that our findings can be useful to educational institutions when considering possible biases that exist in the evaluations of their faculty.

1 Introduction

Do students have different standards when they evaluate their male and female professors? In this paper, we conduct a large-scale quantitative data-analysis study that answers this question in an affirmative way. To this end, we use data from the Rate My Professors website (https://www.ratemyprofessors.com/), henceforth referred to as RMP.

This question is interesting from a sociological viewpoint, as it investigates the role of gender in higher education as well as the perception and expectations of students for professors of different genders. Even though RMP evaluations are not directly used by institutions, we believe that our study provides useful insights on the opinions of students and the behaviors of professors, and therefore can be informative for educational institutions about the possible biases that exist in the evaluations of their professors.

Since the establishment of RMP in 1999, there has been an extensive debate on the validity of online student evaluations, compared to official university evaluations. Despite some anecdotal discrepancies between the two, there has been substantial research that concludes that evaluations on RMP highly correlate with the official university evaluations [4, 14, 21]. As such, a line of research has attempted to analyze the evaluations of RMP to identify gender bias in the ratings assigned by students to their professors [5, 14] and in the language of the reviews [18, 11]. However, prior works use rather small and outdated subsets of RMP and their results do not necessarily represent the biases of contemporary times.

Our analyses rely on a large dataset of evaluations recently collected from RMP. Our data includes all evaluations made by students from 1999 to 2019 (20 years of data). After removing professors that have received less than 5 evaluations, we end up with a dataset consisting of about 4841 US institutions of higher education, 860K professors and 18.5M evaluations.

In a thorough experimental analysis we address a sequence of questions related to gender bias. First, considering the whole dataset we check whether there is any suspicion of gender bias when looking at the overall rating of the different professors. In other words, using a linear-regression model is gender a feature that predicts the overall rating? Our results verify our intuition, which is that the answer to this

*Department of Computer Science, Boston University. {smnikol,josephl, evimaria}@bu.edu
question is affirmative. Even though this question has been addressed by [5, 14], their analyses used an outdated metric of the overall rating that was updated by RMP in 2016. To the best of our knowledge, we are the first to analyze the new overall rating metric and compare the new results to previous ones.

Furthermore, we focus on a set of features that could be important for predicting the gender itself. For this purpose, we use a pre-specified set of professor tags, designed by RMP to represent student perceptions on the teaching style and skills. Using the set of pre-specified professor tags we investigate which ones are strong predictors of the professors’ gender. Our results provide statistically significant evidence that teaching styles related to “extra credit” and “participation matters” have strong positive relationships with female professors; at the same time, “lecture heavy” and “accessible outside class” are more likely to describe male professors.

One may think that pre-specified tags may limit the ability of students to truly express what they think of their professors. Thus, we also conduct an analysis on the actual text of the evaluations by extracting popular adjectives expressing high positive and negative sentiments. Then, we use these adjectives to see if there are differences in the language used in the evaluations for professors of different genders. Our results demonstrate that positive adjectives that are generally frequently used to describe females, such as “wonderful” and “beautiful”, are strong positive predictors of female professors. However, female professors are also positively correlated with other personal traits as well, such as “amazing” and “super”. When negatively described, female professors are more likely to be “rude”, while male professors “arrogant”.

Finally, for each experiment we investigate how the results are affected when considering different university departments, years and states in the US. To the best of our knowledge, we are the first to perform a longitudinal and spatial analysis of gender bias in the overall rating, tags and language of RMP. Our results indicate that over the years, the negative correlation between the female gender and the student ratings seems to strengthen. However, we see that the usage of adjectives for each gender has been changing as well. For instance, the positive strengths of the predictors “wonderful” and “amazing” of female professors have decreased and increased, respectively. Furthermore, for the US states presented in this analysis we demonstrate that gender is a weak predictor of the professors’ overall quality rating. However, language is likely to determine the gender of the professor. For instance, we see that across all states the adjectives “brilliant” and “arrogant” are strongly negative associated with female professors compared to other adjectives.

2 Related Work

In this section we review the related work that studies gender bias in college student evaluations from two main sources: official university evaluations and online evaluations posted on RMP.

2.1 Gender bias in official university evaluations.

There has been strong evidence in historical studies showing that gender bias has a definite effect on student evaluations of teaching. [8] showed that student evaluation ratings were generally positive if the instructor lived up to gender stereotype expectations, and were adversely impacted if they deviated from these stereotypical perceptions. Overall, instructors who adhere to the “gender expectations” are viewed more favorably by their students [1, 3], and in fact student perceptions and evaluations of female faculty are tied more closely to their gender expectations than for male faculty [2]. More recently, the results by [10] indicate that the observed bias was not a result of gendered behavior on the part of the instructors, but of actual bias on the part of the students, since regardless of actual gender or performance, students rated the perceived female instructor more harshly than the perceived male instructor.

The discoveries in our paper have substantial differences compared to the previous work. First, the ubiquitous access to RMP by any student attending a US institution gives us access to a grant variety of data derived from different universities. This allows us to perform larger-scale multivariate analyses that
cannot be performed with the data of a single institution, let alone department. We also process the text in the online evaluations to study the underlying reasons that lead to gender bias.

2.2 Gender bias in online evaluations.

Preliminary research efforts that tried to investigate gender bias in RMP were presented in [5, 15, 20]. To the best of our knowledge Schmidt [18] was the first to study gender bias in RMP at large scale by creating an interactive chart allowing the user to see how different words are distributed across gender and department. The main finding of that experiment was that the adjectives used in the evaluations were strongly influenced by the gender of the professor, with certain adjectives appearing more often in specific-gender professors regardless of their department. A more detailed analysis investigating gender bias across different departments was conducted in [17], where the author compared the average clarity, helpfulness, overall quality and easiness scores of male and female professors in the top 10 most popular departments in RMP and determined the statistical significance of the results. The paper showed that when considering the relationship between the professors’ gender with the average rating criteria, while controlling for teaching department, the results vary significantly by department, even though it is not clear why. Inspired by this finding, our analysis uses the language of the reviews to further comprehend differences between popular departments.

Probably the closest to our work is the analysis presented in [19] that evaluates how gender bias is related to the overall quality score, and to subjective opinions in reviews in RMP on data collected prior to 2016. Similarly to our work, the author uses logistic regression models to find strong predictors that can help in identifying gender inequality. Towards this effort, Sinha considers features related to the text in the reviews, such as sentiment, punctuation marks, and words, to conclude that specific words, such as “sweet”, “person” and “wonderful” are strongly correlated with the gender. A more recent analysis that uses reviews posted before January 2018 is presented in [12]. The authors use linear regression models to identify strong predictors of the overall quality rating and provide the distribution of the overall quality rating for professors possessing some pre-defined tags listed in their RMP profile. However, they do not account for the fact that the overall quality rating metric computation changed after May 18, 2016. Our work follows similar methodologies, but has fundamental differences. First, we study how trends have changed since then, either due to changes on the RMP website, or because of changes in gender bias due to recent times. Also, we provide a detailed analysis on the strength and direction of the tag and adjective predictors of the gender bias across different university departments, years and locations. To the best of our knowledge, this is the first work that performs a spatial and longitudinal analysis of gender bias using the RMP website.

3 Data Collection Methodology and Overview

RMP is a large online platform where students can voluntarily post rated evaluations about university professors, publicly available to other students that are seeking some guidance when selecting courses to take.

3.1 Crawling the dataset

This section describes the methodology used to collect the data for our gender bias study. The simplest way to crawl the data would be to iterate through every professor’s page on RMP using their characteristic tid, i.e., RMP’s internal id number for each professor, and then individually scrape each professor’s information. However, we discovered a more efficient approach that reduced the required crawling time to approximately half. In particular, we discovered that the professors of each university, along with their respective tid, could be provided in convenient JSON formats through making appropriate http requests to Apache Solr.
The only information required to make these requests is the university id, an incremental number, which we continuously increased until we received information about all the universities. Then, for each obtained tid, we made requests to an RMP url that returns all the evaluation-related data for the professor, again in a JSON format. This method, on average, took ~1.7 seconds to extract all the data for a professor as opposed to scraping which took on average ~2.9 seconds. Directly requesting from the website’s back end to retrieve the professors’ raw information significantly improves the efficiency of data collection since this approach overcomes latency factors, such as the time required to load the website’s CSS components and advertisements.

3.2 Extracted Features

Navigating the website is straightforward. A student can query any professor’s name and view the professor’s corresponding RMP page. This page comprises all the information required for our analysis, which we extract and store in the form of features. Certain features are directly extracted from the site, while we engineer the others.

**Directly extracted features.**

A certain set of features can be directly extracted from the information reported on a professor’s RMP page. These features are the following; the professor’s university; the department they are a member of; the average overall quality (OQ) rating ranging from 1 to 5 which since May 18, 2016 is computed as the average of individual student ratings on the professor’s teaching performance, while prior to that it was the average of two other scores, namely helpfulness and easiness that do not exist anymore; the average level of difficulty (LOD) rating ranging from 1 to 5 which is the average of individual student ratings on the difficulty of the professor’s course; the number of evaluations (num. evaluations) posted by the students for the professor; the first date of the professor which denotes the difference in days between May 5, 1999 (establishment of RMP) and the date of the professor’s first comment.

**Engineered features.**

Several of the engineered features are based on the student evaluations posted on the professor’s page. Each evaluation contains a text body with a maximum of 350 characters expressing the student’s opinion on the professor, which we refer to as a comment. Furthermore, each evaluation might also be associated with any of the following pre-defined tags “gives good feedback”, “respected”, “lots of homework”, “accessible outside of class”, “get ready to read”, “participation matters”, “skip class? you won’t pass,”, “inspirational”, “graded by few things”, “test heavy”, “group projects”, “clear grading criteria”, “hilarious”, “beware of pop quizzes”, “amazing lectures”, “lecture heavy”, “caring”, “extra credit”, “so many papers”, and “tough grader”. We now discuss the features that we engineer from the data provided by RMP.

First, we focus on determining the professor’s gender. To this end, we process each professor’s list of evaluations, and from the comments in each evaluation, we compute the number of common male pronouns, i.e., “he”, “him”, “his”, and female pronouns, i.e., “she”, “her”, “hers”. Then, we compute the ratio of the number of male to the number of female pronouns, and if this ratio is greater than 0.95 or less than 0.05, we define the professor’s gender as male, or female, respectively. Otherwise, we leave the professor’s gender undetermined and do not use that data point in our analysis. We found that this process is very precise, and leaves a small percentage of 0.21% professors undetermined. We refer to the corresponding feature as female, which is a binary feature where 1 denotes female and 0 male.

Next, we categorize the professor’s department into STEM (Science, Technology, Engineering, and Mathematics) and non-STEM. To do so we used the list of STEM departments provided by the U.S. Department of Homeland Security. A challenge, however, was addressing the different names that departments have in RMP and in the STEM list, which renders exact matching ineffective. For instance, the same department is listed as “Mechanical Engineering’ in the STEM list, but as “Mech. Engineering’
in RMP. We overcome this obstacle by applying the well-known edit distance method \[16\] that quantifies how similar two strings are to one another by counting the minimum number of operations required to transform one string into the other. Note that the value of this distance alone is not necessarily informative since it can be arbitrarily small or large depending on the size of the strings. Therefore, we followed the steps below. For each professor in RMP we calculated the edit distance of their department to all the fields listed in the STEM list, and for the smallest edit distance found, i.e., the most similar field name in the list, we computed the ratio of the edit distance to the length of the longer word. If this ratio was less than 0.1 we considered the department to belong to the STEM category, otherwise we manually decided its category. We refer to the corresponding feature as \textit{STEM}, which is a binary feature, where 1 denotes a STEM department, and 0 a non-STEM department.

Furthermore, we are interested in the language and the sentiments that students use to express their opinion about male and female professors within their written evaluations. As a result, for each professor, we first extract all \textit{adjectives} from their comments using the Natural Language Toolkit (NLTK) Parts-of-Speech Tagger\[^4\] tool, and then perform sentiment analysis on each adjective using NLTK’s Vader package\[^5\] that returns a sentiment \textit{compound score} for each adjective; adjectives with compound score $\geq 0.05$ are positive and $\leq -0.05$ are negative. The higher (resp. lower) the compound score the more positive (resp. negative) the sentiment of the adjective. We use this score to extract the top 20 most positive and top 20 most negative adjectives by ordering the adjectives from high to low compound score, and taking the top 20 and bottom 20 adjectives. Note that during this process we did not consider any adjective with less than 10,000 site-wide occurrences to only account for adjectives frequently used in the dataset. Each of the top 20 \textit{positive} and \textit{negative} adjectives is a separate feature, whose value is equal to its number of occurrences in the professor’s page.

Finally, we use the tags associated with the evaluations to extract the teaching style of each professor. Each of the 20 \textit{tags} is a separate feature, whose value is equal to its number of occurrences in the professor’s page.

3.3 Dataset Overview

To the best of our knowledge, we have collected the largest and most recent RMP dataset with reviews from academic institutions located in the US posted from September 1999 - November 2019. In all our analyses, we selected to use a subset of the entire dataset containing professors with at least 5 student evaluations to remove “noisy” professor data examples. An overview of the statistics of the collected dataset is presented in Table\[^1\]. Note that the female and male percentages do not add up to 100 because there exist professors with undetermined gender. Furthermore, the column \# Depts. represents the number of unique departments in the STEM and non-STEM lists.

3.4 Feature Preprocessing

After obtaining the final dataset, we performed feature preprocessing prior to any analysis. All categorical data was first transformed into lowercase. In the case of adjectives, we used the Porter Stemmer in NLTK’s Stem package\[^6\] to stem each word. For departments, we converted double spaces, “/”, “and”, and “&” to single space characters, and we removed all punctuation marks.

\[^4\]\url{https://www.nltk.org/}
\[^5\]\url{https://www.nltk.org//_modules/nltk/sentiment/vader.html}
\[^6\]\url{https://www.nltk.org/api/nltk.stem.html}
Furthermore, we performed feature scaling on all real-valued features using standardization, which sets the mean of each feature to 0 and the standard deviation to 1. For this purpose we used Scikit-learn’s preprocessing package.

4 Data Analysis Insights

To demonstrate the applicability of RMP on investigating gender bias, we performed several analyses that provide valuable insights on the data.

How does the frequency of evaluations vary over time?

To the best of our knowledge this is the first study that attempts to understand how the activity on RMP evolved over the years. This provides us a better understanding of the popularity of RMP, and why it is appropriate for gender bias analysis. The distribution of the number of comments over time is shown in Figure 1; the x-axis denotes months through the years 1999-2019; the y-axis shows the number of posted evaluations.

First, we observe a periodic RMP popularity surge occurring during two periods throughout each year: March - April, and October - November. An interesting insight from this result is that students tend to post more evaluations during the semester, as opposed to the end of it. This likely shows that the evaluations are posted when students have vivid impressions on their professors, and before they receive their final grade, which could potentially bias their overall perceptions. This insight is important to our analysis since we expect that student evaluations reflect their true and recent opinions. Second, we see that the popularity of RMP has been increasing over the years, with an average of at least 48311 evaluations every year after 2003.

How does the ratio of male to female professors vary over time?

In the last couple of years, significant efforts have been made to reduce the gender inequality in academia. This is the first study that attempts to comprehend how RMP data can be used to investigate if and how much these efforts have been practically improving the ratio of male to female professors in STEM and non-STEM fields. We define the number of male (resp. female) professors every year to be equal to the number of male (resp. female) professors with at least 1 evaluation received in that year. The ratio of male to female professors over time is shown in Figure 2; the x-axis denotes years; the y-axis shows the ratio of male to female professors. Here, we are considering the ratio of the two genders so normalizing with respect to the number of professors in each gender is not necessary.

Note that the overall ratio of male to female professors in academia decreases over time, thus showing that the activity of female professors over the years seems to be increasing. This decrease is particularly

https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.scale.html
Figure 2: Ratio of male over female professors over time for all, STEM and non-STEM departments.

pronounced for the STEM departments, where we see that from 2003 to 2015 the ratio decreased by \( \sim 0.43 \) as opposed to a decrease of \( \sim 0.37 \) for the non-STEM departments.

**How are professors of both genders being rated?**

Next, we study whether the distributions of OQ ratings across the two genders indicate gender bias. The OQ frequencies have been normalized to account for the different number of reviews in male and female professors. To normalize, we calculate the frequency of each OQ rating per 100 professors for each gender. The distribution of OQ ratings for both, male and female professors is shown in Figure 3; the x-axis denotes the professors’ OQ ratings; the y-axis shows the frequency of professors with that OQ rating.

Figure 3: Normalized frequency of OQ ratings in male and female professors for reviews posted after June 2016.

Previous works presenting results related to the OQ rating demonstrate that the correlation of a professors’ gender with the OQ rating is rather weak [5, 12, 17, 19]. However, all the above works have analyzed datasets with reviews posted before May 18, 2016, and consequently have used the outdated OQ rating metric (see Section 3.2 for further details). Here, we perform a similar analysis using the new definition of the OQ rating. Similar to [12, 19] our first observation is that the OQ distributions of both genders are skewed and that students are more likely to rate professors with higher ratings rather than lower ones. However, in our results we notice that female professors are more likely to receive OQ ratings within the range 1-3 than male professors, while male professors are more likely to receive OQ ratings in the range 3.5-5.

**How are the tags of both genders distributed?**

Next, we study if the frequency of pre-defined tags varies between the two genders to understand
how the students perceive each gender’s teaching style. The tag frequencies have been normalized to account for the different number of reviews in male and female professors. To normalize, we calculate the frequency of each tag per 100 tags for each gender. The distribution of the tag frequency is shown in Figure 4; the x-axis denotes the frequency of tags; the y-axis represents the tags.

Figure 4: Normalized frequency of tags for male and female professors for reviews posted after 2016.

An analysis on the tag distribution of reviews posted before 2016 was presented in [19]. We performed a similar analysis on reviews obtained after 2016 and investigated how much these results have changed. We observe that the tags “gives good feedback”, “caring”, “skip class you wont pass”, “tough grader”, “participation matters”, “get ready to read”, “clear grading criteria”, “lots of homework”, “extra credit” and “so many papers” are encountered more frequently in female than male professors. This finding disagrees with the outcomes in [19], where only the “participation matters” tag is more frequently encountered in female professors. The reasons for these discrepancies can be three-fold; (i) the study in [19] was performed on a dataset obtained at least 4 years ago, therefore not accounting for recent changes in gender bias; (ii) there have been several updates on the tags since then, including renaming, removal and addition; (iii) it is not clear if the frequencies are normalized in [19] to account for the different number of reviews in each gender.

Which are the most popular adjectives in the evaluations?

Adjectives are the most expressive means to convey sentiments. As opposed to tags, they are not limited to fit specific teacher evaluation criteria, which renders them a very useful tool for understanding student perceptions in further depth. Here, we present the frequency of the 20 most positive and negative adjectives in each of the two genders and comprehend to what extent the frequencies are similar. To normalize the number of positive and negative adjectives for each gender, we calculate the frequency of each adjective in the female and male professor per 100 positive and negative adjectives, respectively. The results are shown in Figure 5; the x-axis denotes the frequency of the adjectives; the y-axis represents the adjectives.

We observe that the most frequently used adjectives are common in both genders, indicating that students use similar language to describe male and female professors. For instance, positive sentiments are expressed using words such as “great”, “awesome”, and “super”, while negative sentiments are expressed using words such as “bad”, “horrible”, and “terrible”. Furthermore, we see that for both genders the two most commonly used adjectives are “great” and “bad”. Given that RMP is a website for reviews, these results are intuitive since both adjectives capture in one word the perception of the students for the professors’ performance.
Predicting the OQ Rating using Gender Bias

In this section we focus on the following question: *Is gender a strong predictor of the OQ rating that the professor receives?* This is an important question we need to answer prior to investigating the existence of any bias in RMP. It is essential to first understand which variables are strong predictors of a student’s rating.

Similar to previous works investigating gender bias \[7, 12, 19\] we investigate the relationship between the OQ rating and professor features by formulating this question as an ordinary least square (OLS) regression problem. We set the OQ rating as the dependent variable, and the LOD, number of evaluations, first date, female, and STEM features as independent variables. We examine to which extent our findings hold across different university departments, years and states in the US, by building separate regression models for each analysis on the corresponding subset of professors. All real-valued variables are standardized to have zero mean and unit standard deviation.

Analyzing OQ ratings in the dataset.

We consider three OLS regression models for the OQ rating to account for the fact that since May 18, 2016 students are asked to explicitly rate the OQ of a professor in the submission form. As such, the first dataset considers the entire set of reviews (referred to as All), the second dataset contains reviews obtained before May 18, 2016 (referred to as Pre-2016) and the third dataset contains reviews obtained after June 2016 (referred to as Post-2016). The results of the OLS regression models are shown in Figure 6; the x-axis represents the independent features; the y-axis shows the coefficient of each feature.

Our first observation is that for all three datasets the LOD score is a considerably stronger negative predictor of the OQ rating compared to the other features. An intuitive interpretation is that students tend to assign lower ratings to professors whose courses they feel are hard. Regarding the professor’s gender we observe that being a female professor is a rather weak negative predictor of the OQ rating. In other words, female professors are more likely to receive lower ratings. However, the magnitude of the gender regression coefficient is rather small, and therefore so is its practical significance. We also see that when OQ is directly assigned by students (Post-2016) the magnitude of the negative coefficient increases. Since the definition of the OQ rating is different for the Pre-2016 and Post-2016 datasets, this could be attributed to the fact that when female professors directly receive an OQ score that score is likely to be lower than what they would receive if OQ was the average of the clarity and helpfulness scores (see Section 3.2 for further details). Another underlying cause however could also be that in recent years students are more likely to give higher ratings to male professors. However, the RMP dataset does not provide us with enough information to investigate this hypothesis. Furthermore, we notice that in all three datasets STEM and OQ are anti-correlated, meaning that it is more probable for a professor belonging...
Figure 6: OLS regression using the OQ rating as the dependent variable and different features as independent variables. For each term \( p < 0.001 \). All R-squared = 0.338, Pre-2016 R-squared = 0.325, Post-2016 R-squared = 0.188

| Feature           | Coefficient (Mathematics) | Coefficient (Biology) | Coefficient (Computer Science) | Coefficient (Chemistry) | Coefficient (Engineering) | Coefficient (English) | Coefficient (Psychology) | Coefficient (Business) | Coefficient (History) | Coefficient (Education) |
|-------------------|---------------------------|-----------------------|--------------------------------|-------------------------|---------------------------|-----------------------|--------------------------|------------------------|------------------------|-------------------------|
| (Intercept)       | 3.64***                   | 3.731***              | 3.549***                      | 3.581***                | 3.527***                  | 3.943***              | 3.966***                 | 3.762***               | 3.853***               | 3.975***                |
| num. evaluations  | 0.056***                  | 0.043***              | 0.047***                      | 0.029***                | 0.031***                  | 0.046***              | 0.05***                  | 0.071***               | 0.019***               | 0.047***                |
| LOD               | -0.633***                 | -0.505***             | -0.438***                     | -0.526***               | -0.435***                 | -0.477***             | -0.452***                | -0.493***              | -0.442***              | -0.414***               |
| first Date        | 0.025***                  | 0.015**               | 0.083***                      | 0.01                    | 0.059***                  | 0.077***              | 0.054***                 | 0.079***               | 0.027***               | 0.083***                |
| female            | -0.022*                   | -0.091***             | -0.19***                      | -0.062***               | -0.199***                 | -0.134***             | -0.099***                | -0.123***              | -0.162***              | -0.19***                |
| Num/ Professors   | 48090                     | 28845                 | 16408                          | 17864                   | 10534                     | 53695                 | 26480                    | 17565                  | 21180                  | 9691                    |
| % Female          | 0.381475                  | 0.489513              | 0.258959                      | 0.382229                | 0.160433                  | 0.580724              | 0.57077                  | 0.362141               | 0.340888               | 0.679909                |
| R-squared         | 0.309702                  | 0.22568               | 0.138732                      | 0.22143                 | 0.12099                   | 0.2109                | 0.204284                 | 0.195095               | 0.191057               | 0.132973                |

Table 2: OLS regression models for different departments using OQ ratings after June 2016 as the dependent variable and different features as independent variables. Note: *\( p < 0.05 \); **\( p < 0.01 \); ***\( p < 0.001 \)

to a STEM department to receive a lower rating. It is possible that there are underlying variables not accounted for in the RMP dataset that would explain this phenomenon, such as the gender of the reviewer. We analyze the data as a function of department to study if gender is more pronounced predictor at that level.

Analyzing OQ ratings per department.

Our study is based on the fact that, arguably, the expectations that various subjects raise lead to different student evaluation criteria. Therefore, we investigate if there exist discrepancies between different departments by performing separate OLS regression models on the 10 STEM and non-STEM departments with the most professors. To account for the different definitions of the OQ rating we only present our analysis on reviews posted after June 2016.

Table 2 presents the results of each model, where columns 2-6 correspond to STEM departments and columns 7-11 to non-STEM departments. Our results indicate that gender bias changes from department to department, both in terms of strength as well as direction. In particular, note that the directions of the relationships are almost the same through all departments, but the strengths of these relationships differ. When focusing on the gender predictor of OQ we see that certain departments, such as Computer Science and Engineering, demonstrate a stronger negative correlation compared to other departments, such as Chemistry and Psychology. Two underlying reasons could be the effects of reviewer gender, which is unknown due to the anonymity of RMP and the specific gender stereotypes associated with each discipline. Nevertheless, we can conclude that the OQ scores tend to be influenced by discipline. Furthermore, since we do not observe specific differences when comparing STEM and non-STEM departments, we assume that gender bias in OQ is mainly observed at a departmental level, rather than a more general category of departments (STEM/non-STEM).

Analyzing OQ ratings per year.
We showed that the ratio of male to female professors decreased through the years, a potential indication of less gender bias in professor hirings. After showing that a rather weak negative correlation exists between female professors and student ratings, we are now interested in investigating the evolution of this relationship through the years, and whether the direction and strength of the predictor has changed. However, since the OQ metric changed in May 2016 we focus on comparing results before 2016, and since 2016. The results are shown in Figure 7; the x-axis denotes the years; the y-axis shows the coefficient of each feature. All results are statistically significant, while a coefficient of 0.0 indicates that there is no association between the predictor and the OQ rating.

Results before 2016: We see that the LOD of a course has always been a reason for students to negatively rate a professor. We also notice that since 2003, the strength of the STEM predictor has decreased, meaning that students joining STEM departments assign rating scores closer to what students of non-STEM departments assign in more recent years. Conversely, the negative strength of the female gender predictor of OQ seems to be increasing but the differences are practically indistinguishable, since the magnitude of the coefficient is small.

Results since 2016: Even though the metric of OQ has changed, and therefore so has its interpretation, this is not directly observed in our analysis. In particular, the trends are similar to the ones observed before 2016. The main difference is that the negative magnitude of the female gender regression coefficient seems to be increasing more since 2016. This means that when students are asked to directly assign an overall score to professors they are more likely to give a lower rating to female professors, while this was observed at a smaller level when the overall score was computed as the average of clarity and helpfulness.

Analyzing OQ ratings per state.

Our longitudinal analysis is followed by a spatial one that studies the strength of the regression relationship between the professor’s gender and the OQ rating based on the location. Given that we only consider institutions in the US, we compare institutions located in different states. In particular, we consider 12 states, those with the highest number of reviews. To account for the different definitions of the OQ rating we only present our analysis on reviews posted after June 2016. Our results are shown in Table 3.

First, and similar to our previous results, we observe that there is a negative correlation between the female gender and the OQ score in all 12 states. The strength of this correlation is larger for some states,
such as Ontario and Illinois and smaller for others, such as Ohio and New York. However, overall the coefficients have a relatively small magnitude < 0.1 meaning that the impact of the gender to the rating is small.

6 Gender Bias Analysis

So far our studies have shown that being a female professor has a weak negative correlation with the OQ rating. The uncertainty of the underlying causes leads us to rely on other information found in the online evaluations that could help with further interpreting these results; the main topic of this section. Our investigation on gender bias follows two directions. Initially, we focus on professor tags that students assign in their evaluations, and then we consider sentimental adjectives used in the comments of the evaluations. All real-valued variables are standardized to have zero mean and unit standard deviation.

6.1 Gender Bias in Tags

Here, we address the following question: Is there gender bias in the professor tags? — We answer this question by performing a logistic regression analysis. According to RMP, the utility of professor tags is to allow students to give more specific ratings\(^8\). We are interested in tags because of their ability to concisely represent the perception that students have on the professor’s teaching skills and style, since they were designed for this purpose.

Since in our analysis the perceived gender can be either male or female, we use logistic regression to model the likelihood of observing a specific gender given the professor’s tags as features. In this model, the female gender is the binary dependent variable and the tags are the predictors (20 in total).

Analyzing gender bias in tags in the dataset

Figure 8 presents the results of the logistic regression model using the female gender feature as the dependent variable; the x-axis denotes the tags; the y-axis shows the coefficient of each tag. Among all tags, three describe the professor’s qualities, i.e., “respected”, “hilarious”, and “caring”, as opposed to the others which describe the teaching style of the professor, such as "lots of homework", "group projects", or "get ready to read". The latter group is particularly interesting because it highlights how different gender professors are perceived to teach.

We observe that the tags with the strongest negative coefficients are “respected” and “hilarious”, and therefore their appearance in an evaluation likely describes a male, while the strongest positive coefficient corresponds to “caring”. It is interesting to notice that the tags with the strongest strength are related to the professors personality, rather than their teaching style. This may be attributed to the fact that certain adjectives, such as “caring” in this case, are generally used more often for women, while such distinctions are not known to exist for teaching styles. Regarding the teaching style tags, we observe that female professors are perceived by students to put importance to aspects, such as “participation matters”\(^8\).

\(^8\)https://www.ratemyprofessors.com/blog/buzzpost/professor-tags/
Analyzing gender bias in tags per department.

We now perform our logistic regression analyses on individual STEM and non-STEM departments. It is interesting to see how students from different departments perceive the teaching styles of the two genders, and if similarities or dissimilarities exist.

Table 4 presents the results of each model, where columns 2-6 correspond to STEM departments and columns 7-11 to non-STEM departments. Similar to the results of the single logistic regression model on the entire dataset, we notice that “respected” and “hilarious” are strong negative predictors of female professors, while “caring” is a strong positive predictor.

Furthermore, we also gain some other interesting insights; depending on the department certain tags are either positively or negatively correlated with female professors. Consider “amazing lectures” as an example, even though similar observations can be made for other tags as well. We noticed in Figure 8 that when considering the entire dataset, “amazing lectures” seems almost unrelated to the gender of the professor (coefficient close to zero). However, when investigating gender bias individually for different departments, we observe that it is both a positive (in Chemistry and Psychology) as well as a negative (in Computer Science and English) predictor of the female gender, which shows that we cannot presume the same relationship across all departments. Furthermore, we see that even in fields that are considered close in population, requirements, and teaching material, such as the Computer Science and Engineering departments, student perceptions can still change.

Analyzing gender bias in tags per year.

It was only recently that RMP established tags. In our analysis we observed that tag coefficients have remained approximately the same since their establishment, in terms of significance, strength and direction.

Analyzing gender bias in tags per state.

Table 5 shows the results of the logistic regression model for the 12 states with the most reviews. We observe that our previous findings somewhat also hold when analyzing different states. In particular, we notice that the tags “respected” and “hilarious” are strong negative predictors of female professors across all states, while “caring” is a strong positive predictor. Moreover, we see that these relationships are stronger in some states than others. For example, Pennsylvania and Ohio present coefficients of
higher magnitude compared to the other states for most of the tags, while Texas and Virginia present coefficients of lower magnitude. One interpretation is that in the former states it is more likely that students associate professors with specific traits based on their gender. There could be however other reasons for this phenomenon as well, such as the gender and ethnicity of the students, the professors teaching in these states might exhibit different styles, etc. However, based on the information provided by RMP we cannot effectively control for these characteristics.

### 6.2 Gender Bias in Language

Even though so far we have used the pre-defined tags to link gender bias to certain teaching style characteristics, we believe that investigating potential bias using the content of the comments in the evaluations could provide a different perspective. For this purpose, we use the 20 most positive and 20 most negative adjectives encountered in student evaluations. Next, we ask: Is there gender bias in the adjectives used in the comments? — We answer this question by performing a logistic regression analysis.

We selected adjectives because they capture abstract expressions; a useful tool that tends to express time-independent properties of what is described [6], [9]. An illustrative example demonstrating the preference of abstract expression, and therefore adjectives, is the following. Compare the phrases “the professor is very understanding” and “the professor understood my problem”; the former is more abstract preference of abstract expression, and therefore adjectives, is the following. Compare the phrases “the professor is very understanding” and “the professor understood my problem”; the former is more abstract through the use of an adjective to describe the generalized property that the professor is generally understanding, rather than a concrete example of the professor being understanding once, which is usually depicted through the use of verbs. Since our goal is to understand general student opinions about the two genders, selecting adjectives for our analysis seems appropriate.

We use logistic regression to model the likelihood of a observing a specific professor gender given the adjectives in the professor’s evaluations. To this end, we consider two distinct models, one for the positive and one for the negative adjectives. In both models, the female feature is the binary dependent variable, and the tags as independent variables. Note: *p < 0.05; **p < 0.01, ***p < 0.001.

### Table 4: Logistic regression models for different departments using the female gender as a dependent variable and the tags as independent variables.

| Department        | (Mathematics) | (Biology) | (Computer Science) | (Chemistry) | (Engineering) | (English) | (Psychology) | (Business) | (History) | (Education) |
|-------------------|---------------|-----------|--------------------|-------------|--------------|-----------|--------------|------------|-----------|-------------|
| (Intercept)       | -0.56***      | -0.075*** | -1.17***           | -0.58***    | -1.843***    | 0.353***  | 0.258***     | -0.646***  | -0.744*** | 0.745***    |
| gives good feedback | 0.162***      | 0.133***  | 0.063              | 0.199***    | 0.093***     | -0.097*** | 0.053***     | 0.168***   | 0.021     | 0.093***    |
| respected         | -0.409***     | -0.144*** | -0.607***          | -0.397***   | -0.612***    | -0.262*** | -0.395***    | -0.38***   | -0.438*** | -0.396***   |
| lots of homework  | 0.221***      | 0.222***  | 0.137***           | 0.479***    | 0.068        | 0.152***  | 0.0055***    | 0.108***   | 0.145***  | 0.120***    |
| accessible outside class | -0.112***    | -0.039*** | -0.112***          | -0.154***   | -0.033       | -0.04***  | -0.069***    | -0.087***  | -0.02      | -0.044      |
| get ready to read | -0.14***      | -0.143*** | -0.106***          | -0.156***   | -0.038       | -0.047*** | -0.076***    | -0.041***  | -0.034     | -0.078**    |
| participation matters | 0.071***     | 0.03      | 0.161***           | 0.059***    | 0.061*       | 0.047***  | 0.115***     | 0.025      | 0.121***  | -0.011      |
| skip class you want pass | 0.154***     | 0.128***  | 0.066*             | 0.189***    | 0.035        | 0.057***  | 0.001        | 0.065**    | 0.164***  | 0.139***    |
| inspirational    | -0.105***     | -0.082*** | -0.163***          | -0.141***   | 0.036        | 0.001     | -0.059***    | -0.252***  | -0.025     | 0.009       |
| graded by few things | -0.184***   | -0.159*** | -0.089***          | -0.171***   | -0.045       | -0.095*** | -0.108***    | -0.099***  | -0.051***  | -0.061***   |
| test heavy        | 0.003        | 0.062***  | 0.051*             | 0.094***    | -0.014       | 0.034***  | 0.003        | -0.053***  | -0.018     | -0.033      |
| group projects    | 0.056***      | 0.054***  | 0.028              | 0.047***    | 0.105***     | 0.1***    | 0.123***     | 0.107***   | 0.065***  | 0.073***    |
| clear grading criteria | 0.043*     | 0.047***  | 0.125***           | 0.047*      | 0.132***     | 0.032***  | 0.063***     | 0.039      | -0.029     | 0.111*      |
| hilarions         | -0.675***     | -0.587*** | -0.638***          | 0.733***    | -0.71***     | -0.52***  | -0.466***    | -0.572***  | -0.491***  | -0.251***   |
| beware of pop quizzes | -0.01       | -0.055*** | 0.002              | -0.016      | 0.045        | -0.054*** | -0.003       | -0.055**   | -0.028     | -0.028      |
| amazing lectures  | 0.062***      | 0.094***  | -0.23***           | 0.21***     | 0.121*       | -0.148*** | 0.168***     | -0.008     | 0.01       | 0.098***    |
| lecture heavy     | -0.231***     | -0.143*** | -0.17***           | -0.072***   | -0.096*      | -0.184*** | -0.153***    | -0.177***  | -0.199***  | -0.129***   |
| caring            | 0.653***      | 0.465***  | 0.612***           | 0.584***    | 0.421***     | 0.535***  | 0.507***     | 0.565***   | 0.423***  | 0.336***    |
| extra credit      | 0.069***      | 0.11***   | 0.064*             | 0.061***    | 0.058*       | 0.131***  | 0.178***     | 0.097***   | 0.16***   | 0.053       |
| so many papers    | 0.066***      | -0.003    | 0.023              | 0.08***     | 0.051*       | 0.005     | 0.019        | 0.032**    | -0.043*   | -0.01       |
| tough grader      | 0.021         | 0.118***  | 0.024              | 0.092***    | 0.047        | 0.057***  | 0.103***     | 0.083***   | 0.096***  | 0.160***    |

Num. Professors | 77474 | 43786 | 24889 | 27062 | 16209 | 96966 | 42850 | 28374 | 34176 | 18482 |

% Female | 38.0 | 48.5 | 26.7 | 36.8 | 15.1 | 58.7 | 56.2 | 35.8 | 33.5 | 67.2 |
as predictors. The results are shown in columns 2 and 4 for each model, respectively.

First, we see that most of the coefficients are statistically significant, with the few exceptions being “successful”, “strong”, “mad” and “angry”. Unsurprisingly, certain positive adjectives such as “beautiful” and “wonderful”, which are gender stereotypically used to refer to women, have strong positive coefficient with female professors. Similar claims have been briefly presented at a high level in [11], but we conduct an in-depth analysis specifically on adjectives. However, we see that other more gender-neutral adjectives, such as “amazing”, also exhibit high coefficients. On the contrary, adjectives that are more frequently used to describe male professors are “brilliant” and “great”. Similar observations can be made for negative adjectives as well: “rude” and “unprofessional” occur more frequently in female professor evaluations, and “arrogant” and “bad” in male evaluations.

**Analyzing gender bias in adjectives per department.**

Here, we discuss how adjective coefficients change across different university departments. First, we observed that there exist certain positive adjectives, such as “comfortable” and “successful”, and certain negative adjectives, such as “mad” and “angry” that overall are not statistically significant across different departments. From the predictor variables that are significant, we noticed that the results that hold for all departments generally hold for individual departments as well. This finding is in contrast to our results on the departmental analysis of tag coefficients, where we observed differences among the coefficients between different departments, both in strength and direction.

**Analyzing gender bias in adjectives per year.**

Here, we investigate if the adjectives that students use to describe professors of different genders have evolved through the years. For this purpose we created a logistic regression model for each year, and selected to present the eight positive and negative adjectives with the largest absolute value coefficients averaged across the years 2003-2019. Then, we plot the yearly signed coefficients of these adjectives and the results are shown in Figures 9a and 9b for positive and negative adjectives, respectively.

We notice that even though the strength of certain adjectives, such as “encouraging” (positive) and “unfair” (negative), has not significantly changed through the years, this is not the case for all adjectives. For instance, the positive coefficient of “wonderful” for females has decreased, while the positive coefficient of “amazing” has increased. Another interesting observation is that an adjective such as “brilliant” that refers to a professor’s intelligence and talent, seemed to appear more frequently in male professor evaluations in earlier years, while in more recent years the strength of this relationship has become closer to
Feature ( + Adjective ) | Coefficient | Feature ( - Adjective ) | Coefficient
--- | --- | --- | ---
(Intercept) | -0.222*** | (Intercept) | -0.226***
great | -0.503*** | frustrating | 0.018***
awesome | -0.086*** | rude | 0.156***
onoutstanding | -0.027*** | awful | 0.020***
super | 0.085*** | strong | 0.021***
beautiful | 0.117*** | terrible | -0.01***
amazing | 0.197*** | poor | -0.013***
brilliant | -0.157*** | unfair | 0.034***
successful | 0.085 | sad | -0.008***
wonderful | 0.36*** | disappointed | 0.018***
excellent | -0.054*** | mad | -0.004
happy | 0.032*** | arrogant | -0.226***
perfect | 0.018*** | dumb | -0.008***
fantastic | -0.008*** | unprofessional | 0.067***
positive | 0.06*** | stressful | 0.031***
passionate | -0.022*** | angry | -0.001
encouraging | 0.047*** | stupid | -0.031***
fun | 0.059*** | bad | -0.131***
comfortable | 0.035*** | horrible | 0.039***
strong | 0.001 | negative | 0.031***
few | -0.021*** | brutal | -0.044***

| Num. Professors | % Female | Num. Professors | % Female |
| --- | --- | --- | --- |
| 8,692 | 44.7 | 8,692 | 44.7 |

Table 6: Logistic regression models for positive and negative adjectives using the female gender as a dependent variable and the 20 most positive and 20 most negative adjectives as the independent variables, respectively. + denotes positive and - denotes negative. Note: *p < 0.05; **p < 0.01, ***p < 0.001.

Figure 9: Evolution of logistic regression adjective coefficients over time using the female gender as the dependent variable and 8 positive (left) and 8 negative (right) adjectives as independent variables.

zero. Finally, when focusing on the evolution of negative adjective coefficients, we see that their strengths have remained about the same with no pronounced changes. The only exception can be observed for the negative coefficient of the adjective “arrogant”, whose strength has become weaker recently.

Analyzing gender bias in adjectives per state.

Tables 7 and 8 show the results of the logistic regression models for the 12 states with the most reviews. From these results, we observe that “great”, “awesome”, and “brilliant” have strong correlation with male professors, and “beautiful”, “wonderful”, “encouraging”, and “positive” have strong correlation with female professors across all states. For these adjectives, we see that for some states the coefficients are particularly high or low. For "brilliant", which has the strongest positive association (largest magnitude coefficient) with males among all analyzed adjectives and across all states, we see that this relationship is especially strong in Ohio, Michigan, and Pennsylvania, and weakest in Ontario and New York. Similarly, “beautiful” has the strongest correlation with females in Georgia, Texas, and New York, and the weakest in Ohio. Some adjectives, such as 'fantastic' and 'perfect', present weak correlations as these tags are not always statistically significant and their coefficients are close to zero.
Table 7: Logistic regression results for different states using perceived gender as the dependent variable and the top-20 most positive adjectives as the independent variables. Note: *p < 0.05; **p < 0.01, ***p < 0.001

Regarding the negative adjectives, we observe that 'arrogant' and 'brutal' present a rather strong negative correlation with female professors, while "rude" and "unprofessional" present strong positive correlation with females across all states. Note that "arrogant" has a particularly high coefficient and is strongly associated with male professors across all states, with Georgia, Pennsylvania, Ohio, and Texas having the strongest associations, and Ontario, New York, and New Jersey having the weakest. Moreover, we see that some adjectives, such as "angry", "terrible", and "awful" are not statistically significant and having the strongest associations, and Ontario, New York, and New Jersey having the weakest. Moreover, we see that some adjectives, such as "angry", "terrible", and "awful" are not statistically significant and have coefficients close to zero. One interpretation is that these adjectives are commonly used for both genders.

7 Discussion

In this work we collected and analyzed data from RMP, a popular website which allows college and university students to assign ratings to professors. In this section, we briefly summarize and discuss our key findings.

First, we studied the regression coefficients of several features, including gender, on the rating that a professor receives from the students. Since a new definition of the overall rating metric was introduced by RMP in 2016, this work is the first to analyze and compare how this changed the strength and direction of the gender predictor. Similar to previous claims reported in early 2000 [5, 13] we provide statistical evidence that students are likely to assign better ratings to professors teaching courses that are considered easier. With respect to the gender, we see that being a female professor is negatively correlated with a professor’s received rating, but the strength of gender as a predictor is rather weak. However, in our longitudinal analysis we observed that in recent years the magnitude of the gender coefficient seems to be increasing in the negative direction. Two reasons for this phenomenon might be the following; (i) in contemporary times female professors are more likely to receive lower ratings, (ii) the recent introduction of a new definition of the overall rating metric that requires directly assigning an overall quality score to a professor. Nevertheless, the information provided by RMP is not sufficient to evaluate our hypothesis.

When controlling our experiments for different states in the US we observe that gender is a very weak negative predictor of the rating, and that this result is consistent across all states.

Next, we investigated the existence of gender bias in students’ perceptions of teaching styles, using the professor tags provided by RMP. When our analysis was on all professors, we observed that when
| Feature [- Adjective] | Coefficient (CA) | Coefficient (NY) | Coefficient (TX) | Coefficient (PA) | Coefficient (IL) | Coefficient (GA) | Coefficient (VA) | Coefficient (MI) | Coefficient (ON) | Coefficient (NJ) |
|-----------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| (Intercept)           | -0.081***        | -0.233***        | -0.067***        | -0.188***        | -0.219***        | -0.195***        | -0.168***        | -0.108***        | -0.164***        | -0.447***        | -0.173***        |
| frustrating           | 0.057            | 0.134***         | 0.157**          | 0.196**          | 0.180**          | 0.267***         | 0.242***         | 0.221***         | 0.217***         | 0.273***         | 0.224***         |
| rude                  | 0.196***         | 0.24***          | 0.15***          | 0.117***         | 0.155**          | 0.179***         | 0.267***         | 0.187***         | 0.152***         | 0.101**          | 0.108***         |
| awful                 | 0.042*           | 0.035            | 0.041            | 0.098***         | 0.111**          | 0.097**          | 0.051            | 0.025            | 0.096**          | 0.123***         | 0.097***         |
| wrong                 | 0.022*           | 0.027            | 0.025            | -0.003           | 0.049***         | 0.032            | 0.111***         | 0.019            | 0.076**          | 0.041*           | 0.02          |
| terrible              | -0.022*          | -0.016           | -0.027           | -0.018           | -0.003           | 0.012            | -0.017           | -0.007           | 0.008            | -0.028           | -0.004          |
| poor                  | -0.038*          | -0.02            | -0.002           | -0.056           | -0.124**         | -0.046           | -0.147**         | -0.026           | -0.02            | -0.001           | -0.052          |
| unfair                | 0.114***         | 0.1**            | 0.026            | 0.079            | 0.091*           | 0.155**          | 0.267***         | 0.187***         | 0.152***         | 0.101**          | 0.108**         |
| sad                   | -0.029           | -0.095**         | 0.007            | -0.056           | -0.131           | -0.069           | 0.142            | 0.008            | -0.129           | 0.039            | -0.172          |
| disappointed          | 0.108**          | 0.077            | 0.114*           | 0.152**          | 0.041            | 0.052            | 0.232**          | 0.095            | 0.031            | 0.1              | 0.253***        |
| mad                   | -0.007           | -0.124***        | 0.001            | -0.131**         | -0.039           | 0.007            | 0.118            | -0.002           | -0.007           | 0.006            | -0.096          |
| arrogant              | -0.821***        | -0.723***        | -0.871***        | -0.927***        | -0.957***        | -0.941***        | -0.948***        | -0.918***        | -0.849***        | -0.803***        | -0.761***        |
| dumb                  | -0.081**         | -0.021           | -0.095*          | 0.001            | 0.023            | -0.015           | -0.075           | 0.069            | -0.049           | 0.053            | -0.079          |
| unmotivated           | 0.323***         | 0.368***         | 0.287***         | 0.309**          | 0.382***         | 0.402***         | 0.417***         | 0.274***         | 0.177*           | 0.292***         | 0.317***        |
| stressful             | 0.175***         | 0.181***         | 0.167**          | 0.069            | 0.220***         | 0.055            | 0.019            | -0.0           | -0.002           | 0.117            | 0.208*          |
| angry                 | -0.005           | 0.073            | -0.107           | 0.048            | 0.002            | -0.03            | -0.065           | 0.068            | -0.094           | 0.005            | -0.012          |
| stupid                | -0.003**         | -0.098***        | -0.028           | -0.074**         | -0.079**         | -0.105**         | -0.103**         | -0.068**         | -0.089**         | -0.114**         | -0.085**        |
| bad                   | -0.079***        | -0.079**         | -0.081**         | -0.069**         | -0.105**         | -0.079**         | -0.103**         | -0.068**         | -0.089**         | -0.114**         | -0.085**        |
| horrible              | 0.044***         | 0.038***         | 0.046**          | 0.043**          | 0.069**          | 0.048**          | 0.016            | 0.055*           | -0.003           | 0.022            | 0.107**         |
| negative              | 0.093***         | 0.124***         | 0.045            | 0.117**          | 0.178**          | 0.021            | 0.083            | 0.182**          | 0.076            | 0.131**          | 0.156**         |
| brutal                | -0.249***        | -0.372***        | -0.304**         | -0.087           | -0.341**         | -0.163           | -0.435**         | -0.195           | -0.29**          | -0.265**         | -0.154**        |

| Num. Professors       | 112264           | 72441            | 49936            | 55689            | 34902            | 30560            | 28524            | 22565            | 23321            | 29874            | 27291           |
| % Female              | 47.0             | 43.2             | 47.3             | 46.9             | 43.0             | 44.8             | 43.7             | 47.2             | 46.5             | 45.1             | 38.6            |

Table 8: Logistic regression results for different states using perceived gender as the dependent variable and the top-20 most negative adjectives as the independent variables. Note: *p < 0.05; **p < 0.01, ***p < 0.001

Teaching, females are more likely to pay attention to student participation and are more likely to give extra credit, while male professors seem to be more accessible outside class and grade by fewer things. However, when performing a departmental analysis, where we analyze professors belonging to specific departments separately, these results are not consistent. In fact, there exist teaching styles, such as delivering amazing lectures that are strong predictors of the professors’ gender across many departments, but in different directions. It is possible that there are underlying variables not accounted for in the RMP dataset that would explain this phenomenon, such as the demographics of the reviewer, the stereotypes in different departments, etc.

Finally, we studied whether gender bias exists in students’ perceptions of a professor’s personal characteristics. For this purpose, we separately performed a regression analysis on the most positive and on the top-20 most negative adjectives found in the evaluations. Unsurprisingly, we noticed that positive adjectives that are generally used to describe the female appearances, such as beautiful are strong positive predictors of female professors, while females are negatively described with adjectives such as rude. Interestingly however, in our longitudinal analysis, we discovered that the strength of the adjectives used for each gender seems change over time. For instance, the strength of the positive coefficient for “wonderful” for females has decreased, while the strength of the adjective “amazing” has increased.
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