

# Firms Believing Women Get Less Means They Do

Nagisa Tadjfar

Nancy Wang

April 30, 2025

## Abstract

This paper examines an employer-driven mechanism behind the early-career gender earnings gap using novel data on MIT graduates' job offers and negotiation process. We document three key findings. First, women receive lower initial compensation offers than men within an employer-occupation. Second, this gap is entirely concentrated in non-salary components—signing bonus and equity—with no gap in base salary. Third, we find no gender differences in job search, and women negotiate as frequently and successfully as men. These findings also generalize to a national sample of high-skill workers in a dataset from Levels.fyi. To understand these patterns, we develop a model showing that a small number of discriminatory firms leads *all firms* in the market to lowball women in equilibrium. This market-wide gender gap is sustained through outside offers and cannot be closed by changes in worker behavior. We validate this mechanism using an incentivized resume evaluation experiment with recruiters, where we find that firms expect *other firms* to offer women less. Our results highlight the role of firm behavior—rather than worker decisions alone—in perpetuating gender pay disparities.

---

Tadjfar: Massachusetts Institute of Technology, ntadjfar@mit.edu; Wang: Massachusetts Institute of Technology, wangn@mit.edu. We thank Daron Acemoglu, David Autor, Esther Duflo, Laura Gee, Jonathan Gruber, Nina Roussille, Frank Schilbach, and Rafael Veiel for helpful comments. We received constructive comments from numerous participants at the MIT Behavioral and Labor Lunches and the Yale North East Universities Gender Day. We also thank Jon Daries, Gregory Harris, and Jonathan Schwarz from MIT Institutional Research, Deborah Liverman and others from the Career Advising and Professional Development team, Henry Hannon and Kerri Tierney from the Sloan Career Development Office, and Rajiv Shridhar from Sloan Technology Services for helping us navigate their data and for their insightful comments. We are also grateful to Zuhayeer Musa and Zaheer Mohiuddin for granting us permission to use the Levels.fyi compensation data. We gratefully acknowledge the generous financial support from the George and Obie Shultz Fund at MIT.

# I Introduction

The gender earnings gap remains a focal point in United States policy, spurring a wave of ongoing responses such as pay transparency laws and salary history bans. This gap can be largely, but not entirely, explained by differential sorting into majors, occupations, and industries (Blau and Kahn, 2017). Although the raw earnings gap has narrowed in recent decades, the residual gap unexplained by measurable qualifications persists. A large literature examines various worker-driven explanations such as child penalties (Kleven et al., 2019), pessimism and risk aversion affecting the job search process (Cortés et al., 2023), preferences for flexible work arrangements and other amenities (Mas and Pallais, 2017), the reluctance of women to negotiate (Card et al., 2016; Leibbrandt and List, 2015; Biasi and Sarsons, 2021a), and lower salary expectations (Roussille, 2024). However, several studies also find that information about colleagues’ earnings does not fully close the gender earnings gap (Biasi and Sarsons, 2021b; Cullen and Perez-Truglia, 2023). Other studies similarly find that negotiation interventions have limited efficacy in closing gender earnings gaps (Exley et al., 2020; Cortés et al., 2024). A more nascent literature also documents how HR professionals rely on benchmarking tools to set wages, suggesting that firms have increasingly better information about wage-setting policies at other firms (Cullen et al., 2022).

How might employer beliefs about other firms’ wage-setting policies, particularly for women, affect the gender earnings gap? Outside offers from other employers form an integral part of the bargaining process between a worker and a firm (Caldwell and Harmon, 2019). When employers anticipate the existence of a gender earnings gap at *other firms*, even a well-intentioned firm may lowball female workers relative to otherwise identical male counterparts. Employer beliefs and responses may be particularly important for university students seeking employment after graduation, as many of them receive and decide between multiple offers. Consistent with this mechanism, Kessler et al. (2019) find that recruiters hiring University of Pennsylvania students exhibit no gender-based hiring preferences themselves but believe that other firms do. Despite an extensive literature focusing on how decisions and preferences by women shape the gender earnings gap, less is known about the role of employer beliefs and wage setting policies.

In this paper, we combine novel compensation data from MIT and Levels.fyi with an incentivized resume evaluation experiment and a survey of hiring managers to quantify a residual earnings gap that cannot be explained by occupational sorting, location preferences, negotiation behavior, or expected compensation asks. We leverage a rich dataset of newly-hired MIT bachelor’s and MBA graduates, which provides details on negotiation, job search, and pre- and post-negotiation compensation packages. These data allow us to separate

employer-driven factors from worker-driven factors in gender earnings gaps among high-skill workers. We also link these to detailed administrative variables such as demographics, GPA, degree type, major, and internship history. Our setting offers several attractive features. First, focusing on MIT graduates allows us to consider a relatively homogeneous population and isolate gender differences that are unexplained by educational differences or sorting into disparate roles, firms, or industries. Second, studying new hires permits abstracting away from on-the-job productivity differences. Lastly, this setting sheds light on the real-world negotiation dynamics among workers typically studied in laboratory settings.

We uncover three novel facts regarding gender differences among recent graduates entering high-paying jobs. First, we document a 3% gender earnings gap *within an employer-occupation*, focusing on large employers that hire multiple MIT graduates per degree type each year. These gaps cannot be explained by differences in major, GPA, location choice and whether the individual previously interned at the firm. This gap is also robust to controlling for whether the student negotiated the offer, the number of outside offers, and whether the firm asked for the student’s desired compensation range during the recruitment process. Second, we document a precise zero gap in the base salary within an employer-occupation. In fact, we find that the *entirety of the gap* is driven by differences in non-salary components of the offer, such as signing bonuses, relocation bonuses, and equity. Much of the recent literature on gender pay disparities focuses on base salaries due to the unavailability of non-salary compensation data such as bonuses and equity. Our finding highlights the importance of including these data in examinations of the gender earnings gap. Third, we document a surprising fact: female MIT students are *equally likely* to attempt negotiation as male students in our sample, conditional on accepting similar job offers. They are also equally successful in negotiation, as measured by the percent increase over the initial offer secured through negotiation. We also find no statistically significant gender differences in the number of job applications or outside offers. In our setting, women are lowballed by firms in the initial offers they receive *prior* to negotiation. Despite negotiating as often as men and securing similar percent increases upon negotiation, women are unable to close the gap initialized in the first offer.

Our empirical findings point to the possibility of a self-reinforcing equilibrium: employers expect women to have weaker outside options, which in turn leads firms to make lower offers. In equilibrium, women have diminished bargaining power relative to men despite equivalent credentials and negotiation efforts because of lower outside offers. To illustrate, we develop a simple model of job search and wage setting that allows non-discriminatory firms to arbitrage on lower offers made by discriminatory firms. What are the potential implications on equilibrium wages offered to otherwise identical men and women? Departing from the

Becker (1957) model of discrimination, we focus on an environment where the presence of a few discriminatory firms leads *all* employers to offer lower wages to women, even when most firms are non-discriminatory. In our model, women’s relative wages are determined not by the marginal discriminator but by an arbitrarily small number of discriminatory firms in the market. This generates equilibria in which women are lowballed not just by the discriminatory firm but market-wide. In these equilibria, changes in worker behavior alone cannot close the gender gap; even when women negotiate just as effectively and receive offers at comparable rates to men, the disparity persists. Instead, if firms have sufficient knowledge of other firms’ wage setting policies, the gap can only be closed by the removal of the discriminatory firm.

To directly examine employer beliefs about gender differences in outside offers and discrimination by other firms, we conduct an online experiment with 480 US-based recruiters experienced in hiring MBAs. We generate two versions of each of ten anonymized resumes of Sloan MBA candidates, one with a female name and the other with a male name, holding all other elements of the resumes constant. Each participating recruiter is randomly shown either the female or male version of each resume and asked to guess characteristics of each candidate’s job search process, negotiation process, and compensation outcomes. We incentivize recruiters’ answers with bonus payments for accuracy. We find that recruiters are highly sophisticated and make predictions that are consistent with our findings in the MIT data. Recruiters’ guesses for the initial non-salary component of offers for female resumes are 4% lower than the identical male resumes on average, while there is a precise 0% (with a 95% confidence interval of between  $\pm 1.4\%$ ) difference in their guesses for the initial salary. Additionally, recruiters predict no gender differences in the number of outside offers, the industry composition of the offers, or propensity to negotiate. They also anticipate no changes in the gender earnings gap pre- and post-negotiation. This suggests that, consistent with our model of a firm-driven gender gap, recruiters anticipate lower *outside offer* values for female candidates driven by non-salary components, even in the absence of differences in worker job search behavior.

To assess the broader relevance of our findings, we complement our analysis of MIT students with national data from Levels.fyi on newly hired workers in tech, finance, and consulting. In this sample, we find strikingly similar patterns: gender gaps in base salary are 0 for entry-level hires, while there is a 4% gap in equity and signing bonus. Furthermore, the disparity in non-salary compensation (and to a smaller extent, in salary) grows with experience, both in absolute terms and as a proportion of total pay. This provides external validation of our findings and underscores the importance of including non-salary compensation when documenting gender earnings disparities, especially among high-skill and

experienced workers.

Taken together, our findings offer a novel explanation for the gender wage gap that is *entirely employer-driven*, operating through employer beliefs about outside offers. We find that under imperfect competition, belief among employers that some firms discriminate against women—maliciously or due to incorrect beliefs—is a sufficient condition for an equilibrium in which all employers lowball women. Women will earn less than men even when they sort into identical occupations, exert similar job search and negotiation effort, and secure outside offers from comparable firms. Because employer beliefs alone can sustain this equilibrium, even absent worker misinformation, salary transparency laws and salary history bans cannot eliminate the gender earnings gap. In a similar vein, worker-side interventions such as negotiation coaching or information provision are unlikely to fully close gender pay disparities.

Our paper relates to three main strands of the literature. First, we contribute to the vast literature on gender earnings gaps. Blau and Kahn (2017), Bertrand et al. (2010), and Bertrand (2011) document the history of the gender earnings gap, its continued presence, and its evolution throughout women’s careers. There have been many explanations in the literature for potential drivers of these gaps, including differential preferences for job amenities (Babcock et al., 2017; Mas and Pallais, 2017; Le Barbanchon et al., 2020), differences in educational choices (Buser et al., 2014; Kugler et al., 2021; Wiswall and Zafar, 2021), salary history and transparency (Agan et al., 2020, 2023; Baker et al., 2023; Cullen and Perez-Truglia, 2023; Cullen, 2024; Blundell et al., 2025), differences in job search (Cortés et al., 2023), differences in confidence (Exley and Nielsen, 2024), and differences in salary expectations (Roussille, 2024). Using a combination of rich MIT student data and a resume evaluation experiment with recruiters to rule out worker-driven explanations, this paper builds on previous research by considering an *employer-driven* explanation of the gender earnings gap.

Second, we contribute to the literature on gender differences in negotiation. A large body of evidence, primarily in laboratory settings, examines gender differences in negotiation due to asymmetric retaliation (Babcock et al., 2003; Bowles et al., 2005, 2007; Amanatullah and Tinsley, 2013), negotiation aversion (Babcock et al., 2017; Leibbrandt and List, 2015; Exley et al., 2020; Leibbrandt and List, 2015), and competition aversion (Niederle and Vesterlund, 2007). Outside of the lab, Biasi and Sarsons (2021a,b) find that flexible pay widens gender earnings gaps because women engage in negotiation less frequently than men. More recently, evidence on gender differences in negotiation among high-skill workers has been mixed. Cortés et al. (2024) find that female students at Boston University are less likely to initiate negotiation, but that information interventions do not close the gap. On the other

hand, ? document that in recent years, female MBA students at top universities are *more likely* than male students to attempt negotiation. In this paper, we consider a setting similar to ?, where women and men are equally likely to negotiate, and demonstrate that gender pay disparities can still arise in equilibrium due to employer beliefs about outside offers.

Lastly, our work also relates to the role of outside offers in wage determination. Cahuc et al. (2006) show that workers can increase their earnings by searching for outside offers and either moving to a higher-paying firm or renegotiating with their current firm. Jäger et al. (2024) examine how worker beliefs about outside options can reduce the wages they receive. Caldwell and Harmon (2019) document that differences in networks can affect outside offers and subsequently wages. In this paper, we provide evidence that when the market is not thick, firms making simultaneous offers use knowledge of other firms’ discriminatory wage-setting policies to maximize profits by lowballing women as well, thus sustaining a gender earnings gap.

The rest of this paper proceeds as follows. In Section II, we describe our data sources and sample, and in Section III we use these data to document the within employer-occupation gender pay disparities and motivate a firm-side explanation. Section IV proposes a model in which a gender gap is perpetuated via firm beliefs about outside offers, and Section V provides experimental evidence of firm beliefs consistent with the model. In Section VI, we examine the external validity and potential long-term implications of our findings using a national dataset from Levels.fyi. Section VII concludes.

## II Overview of Data Sources

### II.A MIT Sloan Employment Survey

The MIT Sloan School of Management has one of the leading MBA programs in the United States, with around 200-300 MBAs graduating each year and entering full-time employment. MBA programs have strong recruiting pipelines to major employers, and it is common for large firms to make offers to and hire multiple graduates from the same MBA program into identical positions. Between 2024-2025 alone, more than 25 companies hired three or more Sloan MBA students.<sup>1</sup> MBA programs are required by the MBA Career Services and Employer Alliance (MBA CSEA) to collect detailed post-graduation employment statistics. In addition to the standard reporting fields mandated by MBA CSEA, MIT Sloan collects data on negotiation and outside offers.

Each year, graduating Sloan MBA students are asked to complete an employment survey

---

<sup>1</sup><https://cdo.mit.edu/2024-2025-mba-employment-report/>. Date accessed: April 17, 2025.

administered by the Sloan Career Development Office within three months of graduation. The survey asks students to report the employer name, job title, and location for the accepted offer, as well as detailed information on compensation components, including base salary, equity, signing bonus, and relocation bonus.<sup>2</sup> Students also report which components of the offer they negotiated. Figure A1 shows the survey interface used to collect these data. Because these survey responses are used for post-graduation reporting, the Sloan Career Development Office strongly encourages and incentivizes completion (e.g., via access to graduation tickets). As a result, the survey response rate is estimated to be 99% by the career office. Although responses are available for each year beginning in 2001, we focus our analyses on years 2010-2024 to ensure consistency with our other datasets. Finally, we link survey responses to administrative records on student demographics.

## II.B MIT Graduating Student Survey

Although the Sloan Employment Survey collects data on whether students negotiate various parts of their final offer, it excludes details on the *initial*, pre-negotiation offer students receive and the amount of additional compensation secured as a result of negotiation. To better understand these negotiation dynamics, we turn to data from the MIT Graduating Student Survey (GSS). The GSS is an annual spring exit survey for students earning their bachelor’s and master’s degrees (including MBAs) conducted in March through August each year. The survey is administered jointly by the Career Advising and Professional Development and Institutional Research offices and asks students about their post-graduation plans. Our data include all bachelor’s and master’s student responses collected in the years 2006-2022.<sup>3</sup> Because MBA students were added to the GSS in 2010, we focus our analysis on responses collected between 2010-2022. Students answer detailed questions about the job offer they accepted such as industry, company name, position title, compensation amount broken down by salary, signing bonus, and other components. Students additionally report details about their job search process, including the number of applications they submitted, the duration of their job search, the number of offers they received, whether or not they negotiated various components of their compensation package, and the dollar amount gained from any negotiation. The GSS therefore contains information about initial, pre-negotiation

---

<sup>2</sup>The value of equity is calculated by the Career Development Office as follows: total value of equity units (in points or shares) guaranteed in the offer contract multiplied by the most recent value in USD. For publicly traded companies, the most recent trading value as of the date of survey completion is used. For private companies and start-ups, the most recent publicly disclosed valuation is used.

<sup>3</sup>Note that the Institutional Research office excluded survey data from the years 2017 and 2019 due to privacy concerns because the authors of this paper, Nagisa Tadjfar and Nancy Wang, took the survey and graduated MIT in those two years respectively.

offers of salary and bonus, as well as final, post-negotiation compensation amounts.

The GSS also collects information about students who do not enter full-time employment after graduation, such as those who attend graduate school. We exclude these students in our primary sample and restrict to students who accept job offers in the US. We link these responses with administrative records on student GPA, parental education, ethnicity, gender, and degree type, including departmental information, dual degrees, and other joint programs. Although the participation rate in these surveys varies from year to year, the average participation rate over our sample period is 70%.

## **II.C Levels.fyi**

While our MIT administrative and survey datasets contain many previously unmeasured details about the job search and negotiation process, they face two key limitations. The first is that the data only represent undergraduates and MBA students at MIT. The second is that we only observe job offers for students with little to no prior work experience. In order to examine the external validity of our findings, we extend our analysis to a national sample of job offers between 2018-2023 using de-identified individual-level data from Levels.fyi. Levels.fyi is an online platform and data aggregator that collects individual compensation packages to provide salary benchmarking services for both prospective employers and employees. The compensation data collected by Levels.fyi include both salary and non-salary components, information about the exact position and level within the company, company name, location, and offer date. Data on employee gender and years of prior work experience are also collected. The data are crowdsourced, with users entering their job offers and uploading a verification document such as an offer letter or a pay stub. The dataset contains offer details from over 250,000 individuals, of which around 70,000 are newly hired. We focus our analysis on newly hired individuals in the US, CPI adjust all compensation components to 2022 dollars, and winsorize at 1 percent above and below.

## **II.D Sample construction**

Our main sample from the Sloan data consists of MBA students who accepted a full-time job offer in the US between January 2010 through August 2024. We observe 927 unique employers in our data, around 100 of which hire multiple MBA students per year. On average, around 40% of our sample is female, though the share of female MBA students at Sloan varies from year to year with 31% at its lowest and 47% at its highest in 2024. We CPI adjust all earnings components to 2022 dollars and winsorize at 1 percent above and below.

Our main sample from the GSS data consists of students graduating with bachelor's



degrees or MBAs between 2010-2022. We exclude non-MBA master’s degree students in our analysis, focusing instead on students graduating from an undergraduate program or an MBA program. Around 1-2% of students go on to work for the military after graduation and 37% go on to graduate school. We restrict our sample to students who accepted a non-military offer for full-time employment in the US after graduating from MIT. Because we are focusing on the negotiation process between students and firms rather than the allocation of compensation among founding members, we exclude the 95 students between 2020-2022 who were founders from our analysis.<sup>4</sup> Lastly, we focus our attention on firms that hired three or more MIT students per degree type (bachelor’s or MBA) per year and that hired both male and female students. As with the Sloan data, we CPI adjust all earnings components to 2022 dollars and winsorize at 1 percent above and below. Table 1 presents descriptive statistics for our final sample separately by gender and degree type. Across both the undergraduate and MBA populations, male students earn slightly higher salaries and total compensation than female students on average. However, male and female students appear quite observationally similar in terms of negotiation and job search decisions. Students apply to around 8-12 jobs on average and receive around two offers. In our sample, male students are slightly less likely to be US citizens and ethnically Asian.

### III Evidence from Recent MIT Graduates

#### III.A Documenting the gender earnings gap

To begin, we use the Sloan MBA administrative data to document the gender earnings gap within an employer-location dyad. Although this dataset contains fewer variables on the job search and negotiation process than the GSS, the high survey response rate allows us to examine the gender earnings gap in a non-selected sample. Another advantage of beginning our analysis with MBA students is that MBA programs typically send many graduates each year to the exact same starting position at large firms. This allows us to compare students in the same year starting the exact same job from the same MBA program. We estimate the within-employer gender earnings gap among newly hired Sloan MBA students with the following regression model, using the Poisson pseudo-maximum likelihood estimator:

$$Y_{ifst} = \exp(\beta \cdot \text{Female}_i + \delta_t + \delta_{fs} + \zeta X_i) \epsilon_{ifst}, \quad (1)$$

---

<sup>4</sup>The GSS did not ask students whether they were founders of the company at which they will be employed prior to 2020.

where the outcome variable  $Y_{fst}$  is one of three non-negative measures of compensation for individual  $i$  employed by firm  $f$  at location  $s$  in year  $t$ : (i) total compensation, (ii) base salary, or (iii) total non-salary compensation (sum of bonuses and stock options). The specification includes an indicator for whether the individual is female  $Female_i$ , year fixed effects  $\delta_t$ , and a saturated set of firm-by-location fixed effects  $\delta_{fs}$  to control flexibly for time-invariant heterogeneity in compensation packages across geographic units within employers. By including  $\delta_{fs}$ , we compare outcomes across individuals working for the same employer in the same location. In some specifications, we add individual controls  $X_i$  that may impact the final compensation packages such as whether or not the student interned at the firm, whether the student negotiated the non-salary component of the offer, whether the student negotiated the salary component of the offer, and whether the student had additional outside offers they could have used in the negotiation process. Note that we use the above equation and Poisson pseudo-MLE as recommended by Chen and Roth (2024), since some individuals receive zero bonus or equity. Our results are robust to alternative specifications; we report estimates using OLS in Appendix B.

We report our findings in Table 2. In column (1), we find that within an employer-location dyad, women earn 3% *less* in total compensation, amounting to around \$6,500 on average. To understand what part of the compensation package drives the gender earnings gap, we break total compensation into base salary (column 2) and non-base salary components of the compensation packages such as equity, signing bonus, and relocation bonus (column 3). Strikingly, this gap appears to be driven entirely by a 10-12% gap in non-salary components of compensation, while the base salary gap is a precise zero. In columns (4) through (6), we show that controlling for whether or not the individual interned at the firm, negotiated salary or non-salary components of the offer, or had outside offers does not affect the gender earnings gap in any offer component.

In addition to gender-based earnings disparities, Table A1 documents earnings gaps by race and nationality. We find substantial racial earnings gaps among all major non-white groups—Black, Asian, and Hispanic MBAs. As with the gender gap, these disparities are driven entirely by bonus and equity compensation: compared to white counterparts, Asians earn 9% less, Blacks 21% less, and Hispanics 25% less in non-salary compensation. We also find that international MBAs earn 20% less in bonus and equity than their domestic peers.

While these gaps are both sizable and important, our analysis focuses on gender differences for several reasons.<sup>5</sup> First, the racial minority groups combined represent less than one-third of the MBA sample, whereas 40% of the sample is female. This limits statistical power, especially in more restrictive specifications—such as those limited to firms employing

---

<sup>5</sup>Our results are robust to controlling for race (Section C).

both men and women or both white and non-white workers. Second, stereotypes related to negotiation reluctance are often applied to women. While the racial earnings gaps we observe may stem from similar mechanisms discussed in this paper (e.g., employer beliefs about outside options), a deeper exploration lies beyond our current scope and merits dedicated future study.<sup>6</sup>

Why does the gender gap appear in non-salary compensation instead of salary? In a survey with 70 recruiters, we ask why they thought the gap appears in bonus and not in salary. Most recruiters indicate that salary is fixed for a certain position, whereas bonus is not contracted on. Some direct quotes include:

*I think this is because the salary ranges are typically established for a position, so the variability and bias comes out in bonus and equity. In my hiring experiences, base salaries have to fall within a range regardless of candidate characteristics, so that is probably in play here.*

– Recruiter 1

*Salaries are really more hard set than other forms of compensation. I would feel that most hiring have more flexibility in bonuses because they come from a collective when salaries are more specific to the job demands.*

– Recruiter 2

*Base salary seems to be pretty set in stone when hiring. It is something that really doesn't change very much. Bonus and equity seem to be negotiable though, and is easy to raise or lower depending on the candidate.*

– Recruiter 3

Others say that bonus is more readily hidden, and gender gaps in bonus have less reputational cost for a firm. For example,

*I think that employers know that anyone that they hire has a good idea of what their job salary is thanks to the information out there. For this reason, employers have [to] remain competitive and offer fair salaries if they want to compete in the job market. As a result, they are likely to use the equity and bonus...[to] save money for themselves. Neither appears bad in the court of public opinion, no matter how low it is since it is extra. The same can't be said for a posted salary.*

– Recruiter 4

---

<sup>6</sup>The earnings gap between international and domestic workers may also reflect other factors—for instance, legal barriers faced by international workers or compensating differentials related to costly visa sponsorships.

*The reason is probably optics because as long as a company can say the base salaries women receive are equal to or greater than men, that the company is an equitable place of business. There might even be penalties for not doing that.*

– Recruiter 5

*Bonus and equity can be hidden more easily.*

– Recruiter 6

These reputational costs may be especially salient as states continue to roll out salary transparency laws that do not encompass non-salary compensation such as signing bonus, performance bonus, or equity. This highlights the importance of investigating the full compensation package when documenting gender gaps, especially among experienced workers for whom bonus can account for nearly half of compensation (Section VI).

### III.B Firms lowball women’s *initial* non-salary offers

Next, we turn to the GSS dataset to examine possible mechanisms which may explain the within-employer gap in compensation. The invariance of the gap to controlling for negotiation suggests that differences in negotiation attempts or success are unlikely to be key drivers of the gap. The GSS data allow us to explore this question more directly by looking at whether or not students attempted to negotiate base salary, non-salary compensation components, the initial pre-negotiation offer they received, and the final post-negotiation offer they accepted.

We estimate the pre-negotiation and post-negotiation gender earnings gaps with the following regression model, using the Poisson pseudo-maximum likelihood estimator:

$$Y_{ifsd} = \exp(\beta \cdot \text{Female}_i + \gamma_t + \gamma_{fsd} + \gamma_m) \epsilon_{ifsd}, \quad (2)$$

where the outcome variable  $Y_{ifst}$  is one of four non-negative measures of compensation for individual  $i$  in degree type  $d$  studying major  $m$  employed by firm  $f$  at location  $s$  in year  $t$ : (i) pre-negotiation base salary offer, (ii) pre-negotiation non-salary offer, (iii) post-negotiation base salary offer, or (iv) post-negotiation non-salary offer. The specification includes an indicator for whether the individual is female  $\text{Female}_i$ , year fixed effects  $\gamma_t$ , a saturated set of firm-by-location fixed effects  $\gamma_{fsd}$  to control flexibly for time-invariant heterogeneity in compensation packages across geographic units within employers by degree type, and major fixed effects  $\gamma_m$ . By including  $\gamma_{fsd}$ , we compare outcomes across individuals from the same degree type (bachelor’s or MBA) working for the same employer in the same location. MBA students are all assigned the same major.

Table 3 shows the coefficients on the female indicator for pre-negotiation and post-negotiation offers for both salary and non-salary offers. Looking at columns (1) and (3), we find that the gap in base salary is a precise zero both in the initial offer students receive and the final offer they secure after negotiation. However, we find that women receive lower *initial* offers from firms, particularly in the non-salary component of their compensation. This non-salary gap is quite large at 15%. Comparing column (2) with column (4), we can see that negotiation neither widens nor closes this gap. The large gap in the initial, pre-negotiated offer suggests that the gender gap is primarily due to employers lowballing initial bonus offers to women. Our findings are robust to estimating the regressions using OLS (presented in Appendix B) and to controlling for GPA and race (presented in Appendix C).

These findings challenge the widespread belief that the gender gap stems from differences in how men and women negotiate. Rather, we find that firms offer women lower initial salaries, even before any negotiations take place. Additionally, our results suggest that negotiation behavior does not drive the gap in our setting, as it does not widen post-negotiation.

### III.C Differences in negotiation or job search behavior do not explain the gap

We directly investigate other common worker-driven mechanisms for the gender gap, including willingness to negotiate, effectiveness in negotiation, and job search effort. We estimate the within-employer gender gaps in the following outcomes: whether or not the student negotiated salary and non-salary components of their offer, the total percent over the initial compensation offer the student gained as a result of any negotiation, the number of jobs the student applied to, the number of job offers the student received, how long the student searched for a job before accepting, and the number of weeks the student had to accept the offer. We estimate OLS regressions for these outcomes using the same sample and fixed effects as in Equation (2) and report the estimates in Table 4. This specification allows us to examine whether women who accepted the same job offers as men may have received a lower offer because of differences in negotiation decisions or bargaining power.

In columns (1) and (2), we find that women who accepted the same job offers as men were no less likely to have attempted negotiation. Although this finding may initially appear surprising in light of earlier literature documenting a gender negotiation gap (Leibbrandt and List, 2015; Card et al., 2016; Exley et al., 2020), our finding is in line with ? who find that female MBA students graduating from top programs in the 21st century are, if anything, *more likely* to attempt negotiation compared to their male counterparts. Column (3) also suggests that female students are not any worse at negotiation, reaping similar returns to negotiation as men, where returns are defined as the percent of total compensation gained as a result of a negotiation. Columns (4) and (5) show that women submitted similar numbers

of job applications and received similar numbers of job offers, making it unlikely that the earnings gap can be explained by differences in search effort or number of outside offers they can leverage in the bargaining process. Consistent with Cortés et al. (2023), column (6) shows that female students had a slightly truncated job search window. However, given that the number of outside offers is similar and we are considering gaps among individuals who accepted job offers for the same role, this shorter search window alone is unlikely to explain the gender earnings gap in our setting. Moreover, in our data, we do not find that students who wait longer receive higher offers; rather, the highest job offers arrive earliest in the job application cycle. Lastly, in column (7) we show that women are not offered a shorter window for accepting offers, suggesting that among these workers women are not more likely to face an “exploding offer” than men from the same employers.

Although our findings show that women are lowballed upon receiving an *initial offer*, firms may elicit expected compensation ranges prior to making an offer. When workers provide firms with desired compensation ranges, differences in initial offers may be driven by women providing lower compensation ranges. Roussille (2024) finds that the gender earnings gap for jobs in the tech sector closed entirely once women were shown typical compensation ranges and raised their ask prices accordingly. In order to examine the role of an “ask gap” in our setting, we worked with the MIT administration to add several questions to the 2022 surveys. We examine cross-firm heterogeneity to understand whether this phenomenon is specific to just some firms or across many, and in particular, whether this phenomenon only occurs among firms that ask candidates to provide a “desired compensation range” at any point in the hiring process. The sample size and the number of unique employers in this specification are smaller than in previous analyses because this question was asked only in the 2022 survey; we therefore interpret the results from this analysis with caution.

In 2022, fewer than one in four companies in our sample asked for an expected compensation range. Table A2 shows the gender gaps in initial offers for both salary and total compensation separately for firms that asked for compensation ranges in 2022 and those that did not. Columns (1) and (2) in Table A2 presents initial base salary and total compensation offers respectively among employers that asked for desired compensation ranges, while column (3) and (4) show initial base salary and total compensation offers respectively among employers that did not ask. Comparing columns (1) and (3), we see that the gender gap in base salary is zero among both sets of employers. Columns (2) and (4), however, show that the gender gap in the non-salary components of the offer exists among both sets of employers, though the gap is substantially larger at firms that ask. Our findings suggest that women indeed have lower expectations, particularly for non-salary compensation. However, the gender earnings gap in our setting exists even among firms that do not ask for desired

pay ranges. The contrast between our results and those in Roussille (2024) may be due to various differences in setting, context, and data. First, our setting exclusively considers on-campus recruiting of relatively inexperienced students, while Hired.com is a large online platform used by experienced workers. Second, the MBA graduates in our setting are typically hired to a different set of positions than users on Hired.com, who are predominantly software engineers. Furthermore, the ask gap may be more relevant for some firms than others. For instance, there is a salary level difference of nearly \$40,000 between firms that ask pay expectations and firms that do not ask. This suggests that the practice of asking is concentrated at lower paid firms or in lower paid occupations than those that are more commonly obtained by MIT graduates. Additionally, our data include non-salary compensation (i.e., bonus and equity), which may be influenced by mechanisms other than gender differences in expectations.

Altogether, our results suggest that worker-driven explanations alone are insufficient to explain the gender gap in our setting. We find no gender differences in job search behavior (number of applications, number of job offers, or decision deadline) or negotiation. Furthermore, we find that the gender gap is not entirely a story about women asking for less than men, as a gender gap exists even among firms that do not force women to ask for an initial compensation. Why then do firms make women lower initial offers? In the next section, we propose a simple model to examine conditions that can generate market-wide lowballing of women.

## IV Model

In the previous section, we find limited evidence for worker-driven mechanisms for the gender earnings gap. Here, we introduce a simple model of the gender earnings gap that is driven by firms’ beliefs that other firms are lowballing women. We depart from the Becker (1957) model of discrimination, which shows that in a competitive market with a smooth distribution of prejudice among firms, the least discriminatory firms will hire the discriminated population, and the wage is set by the marginal discriminatory firm. Instead, our model focuses on a non-linear case in which a few bad actors—firms that, whether rightly or wrongly, believe women are less productive than men—exist amid a sea of non-discriminatory firms. We are agnostic as to whether the discrimination is taste-based, statistical, or the result of misinformed beliefs. We then show that if the market is not thick, this results in an equilibrium in which all firms (even unprejudiced, well-intentioned ones) offer women lower initial offers than men. Firms’ market power over women is not driven by gender differences in labor supply elasticities (Robinson, 1969): since the market is not

thick, workers have limited elasticity in both the presence and absence of a discriminatory firm. Instead, market power arises from all firms collectively underpaying women, trapping them in a gender earnings gap equilibrium with no way out.

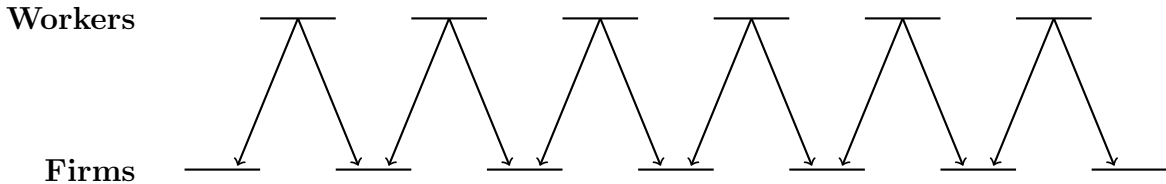
#### IV.A Setup

Let  $\mathbb{Z}^e$  be the set of even integers and firms. Let  $\mathbb{Z}^o$  be the set of odd integers and workers (Figure 1). The ordering of the firms and workers represents horizontal differentiation in skills; the closer the firms are, the more similar they are.<sup>7</sup> A worker  $i$ 's ability if matched with a particular firm  $j$  is

$$a(i, j) = \begin{cases} a & \text{if } |i - j| \leq 1 \\ 0 & \text{otherwise.} \end{cases}$$

This captures the idea that workers have skills that are more applicable to some firms than others. For example, a good candidate for a management consulting firm is likely not a good candidate for a quantitative trading position. Thus, every worker  $i \in \mathbb{Z}^o$  applies to adjacent firms  $j \in \{i - 1, i + 1\}$ , i.e., firms at which they are a close enough fit. Furthermore, this captures the notion that a firm views relevant outside offers as those that come from adjacent competitor firms; for instance, it is unlikely that a management consulting firm would try to compete with wages offered by a quantitative trading firm. We normalize workers' unemployment payoff to 0.

Figure 1: Firms and workers are arranged by similarity



In this model, a game is played by the firms to set wages. At the start of the game, each firm decides a strategy, which is a wage schedule  $(w_{j,1}, w_{j,2})$ ;  $w_{j,1}$  is the wage if the firm hires one worker, and  $w_{j,2}$  is the wage if the firm hires two workers.

After firms set wages, workers then allocate themselves amongst the firms. We assume that workers can coordinate with one another and maximize their individual payoffs, given

---

<sup>7</sup>We call  $j \in \mathbb{Z}^e$  firms, but they could also realistically describe firm-positions. For example, a position for a consulting job at McKinsey might be placed adjacent to a consulting job at the Boston Consulting Group, whereas a position for a quantitative trader at Optiver would be further away. Similarly, an investment banking position at Goldman Sachs might be closer to an investment banking role at J.P. Morgan than it is to a position in HR at Goldman Sachs.



the wages set by the firms. For example, if it would benefit the workers to sort such that two workers go to the same firm, they can coordinate such that they both go to that firm.<sup>8</sup> Workers are also individually rational and can choose to stay out of the labor market if their outside option of unemployment exceeds their payoff from working. After the workers allocate themselves to firms, the wages realize depending on the number of workers allocated to each firm, and firms and workers collect payoffs. A worker's payoff is simply the wage offered by the firm  $j$  that they sort into ( $w_{j,1}$  if she is the only worker at to go to firm  $j$ ,  $w_{j,2}$  if she is one of two workers to go to firm  $j$ ) or 0 if they choose not to work.

In this model, firms directly compete with adjacent “competitor firms” for workers, and each worker only has two competing offers. We believe this to be realistic for two reasons. First, in our sample, we see that workers receive on average two offers (Table 1). Second, it is unlikely that two drastically different firms would be willing to compete with each other. For example, McKinsey would not match an offer for a candidate who is filling a consulting position if they had an outside offer as a software engineer at Google, even if Google offered much more.

Payoffs for firms are determined in the following manner. All firms have productivity  $p$ , and firms set a wage schedule that depends on the number of workers they hire. Firms are profit-maximizing, with the following profit function:

$$\Pi(w_1, w_2) = \begin{cases} 0 & \text{if 0 workers are hired,} \\ ap - w_1 & \text{if 1 worker is hired,} \\ \rho ap - 2w_2 & \text{if 2 workers are hired,} \end{cases} \quad (3)$$

where  $w_1$  is the wage if only one worker joins the firm,  $w_2$  is the wage if two workers join, and  $\rho \in (1, 2)$  captures decreasing marginal returns of a second worker to the same position for the firm.

Suppose there is one firm  $j_0$  that (incorrectly) believes that female workers are less productive than male workers. This firm's payoff for setting  $(w_1, w_2)$  for female workers is

$$\Pi'(w_1, w_2) = \begin{cases} 0 & \text{if 0 female workers are hired,} \\ \alpha ap - w_1 & \text{if 1 female worker is hired, or} \\ \alpha \rho ap - 2w_2 & \text{if 2 female workers are hired,} \end{cases}$$

where  $\alpha \in [0, 1]$  is a measure of how discriminatory the firm is. If  $\alpha = 1$ , then the firm is not

---

<sup>8</sup>While this a strange situation and most often does not happen in real life, we use this to ensure that firms cannot trick two workers into joining the firm with a high  $w_1$  and a low  $w_2$  in equilibrium.

discriminatory against women and views men and women equally. This becomes the case if there are no discriminatory firms in the market. If  $\alpha = 0$ , the firm believes that women have 0 productivity. In the next two sections, we explore the equilibrium wage profiles for women in these extreme cases: first, when there are no discriminators in the market ( $\alpha = 1$ ), and then when there is a maximally discriminatory firm ( $\alpha = 0$ ).

#### IV.B Wages without discrimination ( $\alpha = 1$ )

In this section, we consider the equilibrium wage profile for workers if there are no discriminatory firms, i.e.,  $\alpha = 1$ . In this case, all firms are symmetric, so we only study symmetric equilibria, that is, equilibria where a firm  $j$ 's wage strategy  $(w_{j,1}^*, w_{j,2}^*) = (w_1^*, w_2^*)$ .

**Proposition 1.** *In the absence of any discriminatory firms, all firms will offer wages  $(w_1^*, w_2^*)$  such that each firm gets one worker and each worker is paid  $\omega \in [(\rho - 1)ap, ap]$ . Every firm will receive a payoff*

$$\Pi(w_1^*, w_2^*) = ap - \omega.$$

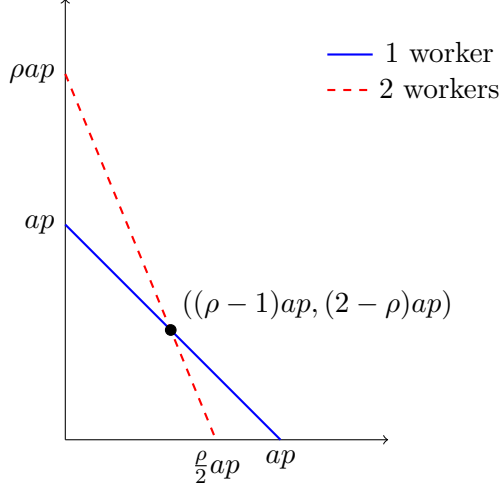
*Proof.* We characterize the set of symmetric equilibria in this game. An equilibrium is characterized by each firm's wage strategies  $(w_{j,1}^*, w_{j,2}^*)$ , the number of workers assigned to each firm, the worker payoffs  $w$ , and the firm payoffs  $\Pi$ . We restrict to equilibria where every firm plays  $(w_{j,1}^*, w_{j,2}^*) = (w_1^*, w_2^*)$  because all firms are symmetric. To characterize the set of equilibria, we focus on the following cases:

1. Consider strategies where  $w_1^* = w_2^* = \gamma$ . We show that in equilibrium,  $\gamma \in [(\rho - 1)ap, ap]$ .

We begin by showing that  $\gamma \in [0, (\rho - 1)ap)$  are not equilibrium wage strategies. If all firms play this strategy, each firm would attract one worker (each firm would arbitrarily attract the worker from the left or the worker from the right, since workers coordinate with one another) and earn profits  $\Pi(\gamma, \gamma) = ap - \gamma$ . However, each firm would prefer to attract two workers instead of one at the wage of  $\gamma$ . Thus, a firm  $j$  has incentive to deviate from this strategy by instead playing  $(w_{j,1}^*, w_{j,2}^*) = (\gamma, \gamma + \varepsilon)$ . With this strategy, the firm would attract two workers and earn payoff  $\Pi(\gamma, \gamma + \varepsilon) = \rho ap - 2(\gamma + \varepsilon) > \Pi(\gamma, \gamma)$ .

We note that  $\gamma = (\rho - 1)ap$  is an equilibrium with each firm attracting one worker, each worker is paid  $(\rho - 1)ap$ , and each firm earns  $ap - (\rho - 1)ap = (2 - \rho)ap > 0$ . Intuitively,  $(\rho - 1)ap$  is the wage at which a firm is indifferent between attracting one worker or two workers (Figure 2). For wages below  $(\rho - 1)ap$ , the firm would prefer

Figure 2: Profit as a function of wage and number of workers hired



NOTES.— Firm profit as a function of wage and number of workers at the firm. The intersection of the two lines indicate the wage at which firms are indifferent between two workers.

to attract two workers. For wages above  $(\rho - 1)ap$ , the firm would prefer to attract a single worker. Thus, if every firm plays  $(w_1^*, w_2^*) = ((\rho - 1)ap, (\rho - 1)ap)$ , there is no incentive to deviate. Increasing  $w_1$  would clearly lower profits, increasing  $w_2$  would cause a firm to attract two workers but result in lower profits, decreasing  $w_1$  would result in the firm attracting 0 workers since the worker it would have attracted would instead go to the adjacent firm, and decreasing  $w_2$  would not affect how workers sort or profits. Thus,  $(w_1^*, w_2^*) = ((\rho - 1)ap, (\rho - 1)ap)$  is an equilibrium.

Using similar logic,  $\gamma \in ((\rho - 1)ap, ap]$  are equilibria. In these equilibria, each firm attracts one worker, the worker is paid  $\gamma$ , and the firm receives profits  $ap - \gamma \geq 0$ .

Finally, firms would never set  $\gamma > ap$ , which is the wage at which the firm would earn 0 profits with a single worker.

2. We next consider strategies where  $w_1^* > w_2^*$ . In this set of potential equilibria, workers prefer to sort so that there is one worker per firm. Also, to satisfy workers' individual rationality constraints and to ensure that the firm makes weakly positive profits,  $w_1^* \in [0, ap]$  and  $w_2^* \geq 0$ . The set of equilibria defined by this structure are  $0 \leq w_2^* < w_1^* \in [(\rho - 1)ap, ap]$ .

Note that  $w_1^* \in [0, (\rho - 1)ap)$  are not equilibria. In this range of  $(w_1^*, w_2^*)$ , a firm  $j$  would always prefer two workers and could deviate by setting  $w_{j,2} = w_1^* + \varepsilon$  to attract two workers and increase its payoff.

All strategies where  $w_1^* \in [(\rho - 1)ap, ap]$  and  $w_2^* \in [0, w_1^*)$  are equilibria in which each firm attracts one worker at  $w_1^*$  and earns payoff  $ap - w_1^* \geq 0$ . Although a firm  $j$  would prefer to attract two workers at  $w_2^* \in [0, (\rho - 1)ap)$ , there is no way to attract a second worker unless  $w_{j,2} > w_1^* \geq (\rho - 1)ap$ , which would decrease the firm's payoff. Furthermore, setting  $w_{j,1} > w_1^*$  strictly decreases payoffs, and setting  $w_{j,1} < w_1^*$  causes the firm to lose their only worker, resulting in  $\Pi = 0$ .<sup>9</sup> Thus, there is no profitable deviation.

3. Finally, we consider the set of strategies where  $w_1^* < w_2^*$ . Here, workers prefer to sort such that firms alternately attract either zero workers or two workers. Ex ante, firms do not know whether they will receive zero or two workers (depending on in which direction the workers sort). With two workers, firms would set  $w_2^*$  to be bounded above by  $\frac{1}{2}\rho ap$ , above which firms would earn negative profit from employing two workers. We show that there are no equilibria where  $w_1^* < w_2^*$ .

Consider  $w_2^* \in ((\rho - 1)ap, \frac{1}{2}\rho ap]$ , where the firm  $j$  would prefer to hire a single worker instead of two workers. The firm  $j$  could deviate profitably by setting  $w_{j,1} = w_2^*$  and  $w_{j,2} < w_2^*$  to attract a single worker. So  $w_1^* < w_2^* \in ((\rho - 1)ap, \frac{1}{2}\rho ap]$  are not equilibria.

If  $w_1^* < w_2^* \in [0, (\rho - 1)ap]$ , the firm would prefer to hire two workers. However, the firm is unsure whether the workers will sort such that they receive two workers or zero workers. Instead, firms know that the labor supply comes from a mixed strategy where with probability  $\theta$ , workers sort such that every firm  $j = 2z^o$  (where  $z^o$  is an odd integer) gets two workers, and every other firm  $j = 2z^e$  (where  $z^e$  is an even integer) gets zero workers; these firms also expect that  $j = 2z^o$  firms get zero workers and  $j = 2z^e$  firms get two workers with probability  $1 - \theta$ . Thus, a firm  $j$ 's expected profits from a wage strategy  $w_1^* < w_2^*$  is

$$\mathbb{E}[\Pi \mid w_1^*, w_2^*, w_1^* < w_2^* \in [0, (\rho - 1)ap]] = \begin{cases} \theta \cdot (\rho ap - 2w_2^*) & \text{if } j = 2z^o \\ (1 - \theta) \cdot (\rho ap - 2w_2^*) & \text{otherwise.} \end{cases} \quad (4)$$

We investigate whether a firm would prefer to deviate from this strategy in equilibrium. We focus on  $\theta \in [0, 1/2]$ , where a firm  $j = 2z^o$  has a probability  $\theta \in [0, 1/2]$  and a firm  $j = 2z^e$  has probability  $1 - \theta \in [1/2, 1]$  of receiving 2 workers. We propose a deviation in which a firm  $j = 2z^o$  instead plays  $w_{j,1} = w_2^* + \varepsilon$ . With this deviation, the firm

---

<sup>9</sup>Since workers can discuss with one another prior to sorting to firms, this deviation would cause all workers to the right of the deviating firm to sort to the firms to the right, and all workers to the left of the deviating firm to sort to the firms to the left, leaving the deviating firm without a worker.

(which would have attracted zero workers with probability  $\theta \in [0, 1/2]$ ) would result in the firm hiring one worker at wage  $w_{j,1} = w_2^* + \varepsilon$ . This deviation is profitable if

$$\begin{aligned} & \mathbb{E}[\Pi \mid w_1^*, w_2^*] < \Pi(w_2^* + \varepsilon, w_2^*) \\ \iff & \theta \rho a p - 2\theta w_2^* < a p - w_2^* - \varepsilon \\ \iff & w_2^*(1 - 2\theta) < a p(1 - \theta \rho) - \varepsilon. \end{aligned}$$

Since  $w_2^* \leq (\rho - 1) a p$ , it is sufficient to show that

$$\begin{aligned} & (\rho - 1) a p(1 - 2\theta) < a p(1 - \theta \rho) - \varepsilon \\ \iff & (\rho - 1)(1 - 2\theta) < 1 - \theta \rho - \frac{\varepsilon}{a p} \\ \iff & \rho - 2\theta \rho - 1 + 2\theta < 1 - \theta \rho - \frac{\varepsilon}{a p} \\ \iff & \rho - \theta \rho + 2\theta < 2 - \frac{\varepsilon}{a p} \\ \iff & \rho(1 - \theta) + 2\theta < 2 - \frac{\varepsilon}{a p}. \end{aligned}$$

Given that  $\theta \in [0, 1/2]$  and  $\rho \in (1, 2)$ , the left side of the inequality is maximized when  $\theta = 1/2$ . Then

$$\begin{aligned} \rho(1 - \theta) + 2\theta & \leq \frac{1}{2}\rho + 1 \\ & < 2 - \frac{\varepsilon}{a p}, \end{aligned}$$

where the second inequality holds since  $\rho \in (1, 2)$  and  $\varepsilon$  is arbitrarily small. Therefore,  $\mathbb{E}[\Pi \mid w_1^*, w_2^*] < \Pi(w_2^* + \varepsilon, w_2^*)$  for  $\theta \in [0, 1/2]$  and firm  $j = 2z^o$ , i.e., the deviation is profitable for some firm  $j = 2z^o$ . By symmetry, for  $\theta \in (1/2, 1]$ , a firm  $j = 2z^e$  would prefer to deviate.

Thus, we have shown that  $w_1^* < w_2^* \in [0, (\rho - 1) a p]$  are not equilibrium strategies.

Overall, we have shown that the symmetric equilibria in this game are the following:

- 1)  $w_1^* = w_2^* = \gamma$ , where  $\gamma \in [(\rho - 1) a p, a p]$ , and
- 2)  $0 \leq w_2^* < w_1^* \in [(\rho - 1) a p, a p]$ .

In each of these equilibria, firms offer wages  $(w_1^*, w_2^*)$ , and each firm gets one worker. Payoffs for workers and firms are  $\omega \in [(\rho - 1) a p, a p]$  and  $\Pi(w_1^*, w_2^*) = a p - \omega$ , respectively.  $\square$

#### IV.C Wages in the presence of a discriminatory firm ( $\alpha = 0$ )

In the previous section, we showed that if there are no discriminatory firms, all workers regardless of gender are paid  $w_{\text{no disc}} \in [(\rho - 1)ap, ap]$ . How does this wage profile change in the presence of a discriminatory firm in the market? Here, we show that each worker  $i$  in the market, regardless of whether she interacts directly with the discriminatory firm, will be paid  $w_{i,\text{disc}} < w_{\text{no disc}}$ . We focus on the most extreme case ( $\alpha = 0$ ) where a firm  $j_0$  believes women are not productive.

**Proposition 2.** *In the presence of a discriminatory firm with  $\alpha = 0$ , all workers are paid strictly less than  $(\rho - 1)ap$ , i.e., the lowest equilibrium wage in a market without discrimination.*

*Proof.* We begin with firm  $j_0$ 's optimal wage strategy for female workers. Since the firm  $j_0$  believes women have productivity  $\alpha a = 0$ , the firm will offer  $(w_{j_0,1}^*, w_{j_0,2}^*) = (0, 0)$ .

Consider firms  $j = j_0 \pm 2$ , i.e., the firms adjacent to the discriminatory firm  $j_0$ . For these firms, there is no profitable deviation from  $w_{j,1}^* = 0$  (or  $\varepsilon$ ). In particular, firm  $j$  knows that it can always attract the worker whose outside option is  $(0, 0)$  from firm  $j_0$ . Thus, if firm  $j$  attracts only one worker, it would weakly prefer to attract the worker whose outside offer comes from the discriminatory firm  $j_0$ . Given that the firm  $j$  can attract a single worker at  $w_{j,1}^* = 0$ , they would then set

$$w_{j,2}^* \leq \frac{1}{2}(\rho - 1)ap,$$

where the right side is the wage for two workers at which the firm is indifferent between two workers at  $w_{j,2}^*$  or one worker at  $w_{j,1}^* = 0$ . Because we are interested in the upper bound of what a worker can earn when  $\alpha = 0$ , let  $w_{j,2}^* = \frac{1}{2}(\rho - 1)ap$ .

Now consider  $j = j_0 \pm 4$ , i.e., the firm that is adjacent to the previous firm. In order to attract one worker at the lowest cost, the firm needs only to offer the single worker wage  $w_{j,1}^*$  to match the second worker wage from firm  $j_0 \pm 2$ , i.e.,  $w_{j_0 \pm 4,1}^* = w_{j_0 \pm 2,2}^* + \varepsilon$ . Furthermore, just as the firm  $j_0 \pm 2$  did, the firm offers a wage for two workers that is less than or equal to the wage that would make the firm indifferent between one or two workers. Thus,

$$\begin{aligned} w_{j_0 \pm 4,1}^* &= w_{j_0 \pm 2,2}^* \leq \frac{1}{2}(\rho - 1)ap, \\ w_{j_0 \pm 4,2}^* &\leq \frac{3}{4}(\rho - 1)ap. \end{aligned}$$

Again, since we are interested in the upper bound of worker wages, let  $w_{j_0 \pm 4,1}^* = \frac{1}{2}(\rho - 1)ap$  and  $w_{j_0 \pm 4,2}^* = \frac{3}{4}(\rho - 1)ap$ .

Continuing in this same manner for  $j = j_0 \pm 6, 8, 10, \dots$ , we arrive at the following upper bounds for the wage strategies, which depends on the distance of firm  $j$  to the discriminatory firm  $j_0$ :

$$\begin{aligned} w_{j,1}^* &\leq \max \left\{ \left(1 - \frac{1}{2^{n_1}}\right) (\rho - 1)ap, \quad 0 \right\}, \\ w_{j,2}^* &\leq \left(1 - \frac{1}{2^{n_2}}\right) (\rho - 1)ap, \\ \text{where } n_1 &= \frac{|j - j_0| - 2}{2} \quad \text{and} \quad n_2 = \frac{|j - j_0|}{2}. \end{aligned}$$

Note that since  $n_1$  and  $n_2$  are positive, both  $w_{j,1}^*$  and  $w_{j,2}^*$  are strictly less than  $(\rho - 1)ap$ .  $\square$

The intuition for this solution is that each firm sets wages based on the worker's best outside option. Firm  $j$ 's wage offer for a single worker  $w_1$  is equal to the wage offer  $w_2$  that the adjacent firm is offering to the second worker at the firm (which is the outside offer for the first worker at firm  $j$ ). Concretely, the firm  $j_0$  will offer  $(w_{j_0,1}^*, w_{j_0,2}^*) = (0, 0)$  since they perceive the worker's productivity to be 0 (since  $\alpha = 0$ ). Knowing this, the adjacent firms  $j_0 \pm 2$  arbitrage on this weak outside offer and offer  $(w_{j_0 \pm 2,1}^*, w_{j_0 \pm 2,2}^*) = (0, \frac{1}{2}(\rho - 1)ap)$ . Note that  $w_{j_0 \pm 2,2}^*$  is set to be the wage at which the firm is indifferent between one or two workers, given  $w_{j_0 \pm 2,1}^*$  (Figure 2).

We also conjecture that one equilibrium is for each firm  $j$  to offer the upper bound of the above, i.e.,

$$\begin{aligned} w_{j,1}^* &= \max \left\{ \left(1 - \frac{1}{2^{n_1}}\right) (\rho - 1)ap, \quad 0 \right\}, \\ w_{j,2}^* &= \left(1 - \frac{1}{2^{n_2}}\right) (\rho - 1)ap, \\ \text{where } n_1 &= \frac{|j - j_0| - 2}{2} \quad \text{and} \quad n_2 = \frac{|j - j_0|}{2}. \end{aligned}$$

In this equilibrium, each firm except the discriminator  $j_0$  will attract one worker, and each worker  $i$  will receive a payoff  $w_i = \max \left\{ \left(1 - \frac{1}{2^n}\right) (\rho - 1)ap, \quad 0 \right\}$  where  $n = \frac{|i - j_0| - 1}{2}$ . Furthermore, each firm will receive a payoff of

$$\Pi(w_{j,1}^*, w_{j,2}^*) = \begin{cases} \left[1 - \left(1 - \frac{1}{2^{n_1}}\right) (\rho - 1)\right] ap & \text{if } j \neq j_0 \\ 0 & \text{otherwise.} \end{cases}$$

Note that this wage strategy is an equilibrium. The logic is similar to that in Section IV.B. No firm has incentive to increase  $w_{j,1}^*$  because this would decrease profits. Furthermore, a firm

$j$  also has no incentive to decrease  $w_{j,1}^*$ . Recall that the adjacent firm  $j'$  offers  $w_{j',2}^* = w_{j,1}^*$ ; if firm  $j$  decreased  $w_{j,1}^*$ , the firm's worker would instead go to the adjacent firm  $j'$  to avoid a wage decline. Then firm  $j$  would receive 0 payoff. Furthermore, the firm  $j$  has no incentive to deviate from  $w_{j,2}^*$ . Increasing  $w_{j,2}^*$  would attract two workers to the firm; since  $w_{j,2}^*$  is the wage at which the firm is indifferent between one worker or two workers, such a deviation would result in lower profits. Additionally, the firm would weakly prefer to not decrease  $w_{j,2}^*$ , as this would not change the allocation of workers or payoffs in equilibrium.

In this equilibrium, the wage profile for workers  $i \in \mathbb{Z}^o$  is characterized by

$$w_i = \max \left\{ \left( 1 - \frac{1}{2^n} \right) (\rho - 1)ap, \quad 0 \right\} \quad \text{where} \quad n = \frac{|i - j_0| - 1}{2}.$$

Recall from Section IV.B that the lowest wage offered under no discrimination is  $(\rho - 1)ap$ . Thus, the wage offered to a worker under discrimination is strictly lower than that offered in this equilibrium with discrimination. Furthermore, as the distance between a worker and the discriminatory firm grows, the gap between the wage offered under discrimination and under no discrimination shrinks.

Central to this model is the assumption that each worker only receives offers from her two adjacent firms. We justify this in two ways. First, we note that if we assume the market is not thick, then the worker should receive a finite number of offers. Second, in our sample of MIT graduates, we find that the average number of job offers received is two. This is the case for both men and women (Table 4). Thus, our model in which each worker only receives offers from her adjacent firms may be realistic, especially in this sample of students searching for full-time jobs after graduation.

This model illustrates how the gender wage gap can be perpetuated entirely by firms. When firms make offers to men, they operate as if under the *no discrimination* case. However, with the knowledge that there is even a single firm that is prejudiced against women, the firms can lowball women and create a market-wide gender gap. Unlike many worker-side mechanisms (e.g., misinformation about wages, risk aversion) for the gender gap, the firm-driven gap cannot be closed by changing the behavior of female workers. Instead, it requires the removal of the discriminatory firm, or a shift in the beliefs of non-discriminatory firms about whether there exists a discriminatory firm in the market. In the next section, we examine this necessary condition—that the firms believe that other firms are discriminating against women—directly in a resume evaluation experiment with recruiters.



## V Experimental Evidence for Model Mechanisms

Outside offers are an important input to any offer made by a firm. In most models, firms make offers based on the value of the worker and competing wages set by other firms. In Section IV, we show that if firms are aware that women have lower outside offers, they will subsequently offer women lower initial offers. This requires that firms know that women are being lowballed by other firms so that they can set their wage offers accordingly.

Are firms aware of other firms' wage-setting policies? In this section, we conduct an experiment to measure firm beliefs about workers' outside offers and job search behavior and whether these beliefs differ by worker gender. We ask MBA recruiters to evaluate ten resumes based on resumes from real Sloan MBA candidates. Recruiters are asked to guess, in an incentivized manner, the nature of the candidates' best outside offer and general job search behavior. We find that recruiters are well-informed and predict several key patterns that we observe in the MIT MBA student data. First, they anticipate a 4.6% gender gap in initial non-salary offers. Moreover, recruiters do not perceive a gender gap in salary or in the job search process (e.g., negotiation propensity, negotiation efficacy, number of offers received, or industry from which offers come). This supports the idea that firms do not lowball women due to perceived gender differences in job search. Instead, firms are aware of other firms' wage-setting policies and believe that other firms are lowballing women. This gives firms the opportunity to increase profits by arbitraging on this perceived gender gap in outside offers by lowballing women as well.

### V.A Experimental design

To examine whether firms anticipate gender gaps in the offers that workers receive pre- and post-negotiation, we conduct a incentivized resume evaluation experiment with MBA recruiters.<sup>10</sup> Using Prolific, we hire 480 recruiters with experience hiring MBAs to evaluate ten resumes (Table A3).<sup>11</sup> Recruiters are paid an average of \$8/hour with a median survey completion time of 42 minutes.<sup>12</sup> 92% of our sample is employed full-time, and 80% work at private for-profit firms. Furthermore, the recruiters work for large and reputable firms; the average firm size is over 400, and 40% of the recruiters work at Fortune 500 companies. The recruiters are also active; nearly everyone hired someone in the past year, and the average number of hires in the past year was 5.6. Over half of the sample mostly hires MBA

---

<sup>10</sup>This experiment was registered in the AEA RCT registry (ID: AEARCTR-0015057).

<sup>11</sup>Prolific is a commonly used platform for recruiting participants in economics research. All participants on Prolific go through a robust onboarding process and bank-grade identity check to ensure that they are who they claim to be.

<sup>12</sup>This pay rate is comparable to the average pay on Prolific.

candidates. Finally, our sample is 41% female, majority white (62%), and majority identify as politically conservative (56%).

After answering questions about their hiring experience, recruiters are asked to evaluate the ten anonymized resumes from MIT Sloan MBA candidates who had applied to and received full-time positions within the last few years. Recruiters are asked to give their best guess about characteristics of each candidate’s job search process and outcomes. Specifically, recruiters are asked to guess the MBA candidate’s compensation package (salary, signing bonus, equity) both pre- and post-negotiation, the likelihood that the candidate negotiated various components of their compensation package (salary, signing bonus, equity, location, flexibility) on a five-point likert scale, the candidate’s tenure at the firm, the number of offers the candidate received, and the industries from which these offers came. All guesses are incentivized, with the exception of the industries from which a candidate received a job offer since it does not have a numerical answer. For all other guesses, the recruiter receives a bonus payment of \$0.10 if they guess within a 5% margin of the true answer.<sup>13</sup> Under this incentive scheme, participants are eligible for up to \$8 in bonus pay. To reduce noise in the recruiters’ guesses for compensation, recruiters are also shown an infographic about the distribution of compensation packages received by recent Sloan MBA graduates (Figure A2). This infographic is taken from a publicly available brochure from MIT Sloan and contains information about the mean (\$159,391), median (\$165,000), minimum (\$62,000), and maximum (\$270,000) base salary; the median signing bonus (\$30,000); and the share of students who received a signing bonus (70.6%).

Resumes are created using a resume template provided by the MIT Sloan Career Development Office. Each resume has sections detailing education, work experience, and other information. All experiences are drawn from real Sloan MBA resumes provided by the Career Development Office, although firm names are changed to comparable firms in the same industry to preserve anonymity. The resumes are designed to represent the major sectors targeted by Sloan MBAs (approximately 40% consulting, 30% finance, 20 % tech, 10% biotech). Using this process, we generate a total of ten unique resumes.

Each resume is then assigned a particular race, after which two versions (male and female) are generated (Figure A3). The racial breakdown (40% white, 20% Asian, 20% Black, and 20% Hispanic) is approximately based on the demographic composition of Sloan MBA students in 2023. Then, we create a male and a female version of each resume, where

---

<sup>13</sup>Although the resumes are heavily inspired by real MBA candidates’ resumes, due to anonymization, we are unable to incentivize using the candidates’ true compensation. Instead, we use pilot studies, in which we ask recruiters to make “offers” to these candidates, as a benchmark for the truth for offers received by the candidate. However, recruiters in our study are not told that the offers received by these candidates are from Prolific recruiters.

the gender is indicated via the first name atop the resume. To generate realistic first and last names reflecting both gender and race, we use Bayesian Improved Surname Geocoding (Rosenman et al., 2023).

## V.B Recruiter beliefs

In this section, we show regressions where compensation is the dependent variable following Equation (1). All equations include fixed effects for resume ID, resume order, recruiter, and recruiter demographics such as race and gender. All compensation values (total compensation, salary, and non-salary compensation) are winsorized at the 5th and 95th percentiles.

We report the regression results in Table 5. We find that recruiters believe that women’s outside offers are lower than men’s outside offers (columns 1 and 2). Mirroring our results from the MIT observational data, the recruiters believe there is a precise zero gap in salary (on a mean of \$146,300). Moreover, the recruiters believe that the gender gap is driven by initial non-salary compensation, with a 4.6% gap on a mean of \$54,600. Furthermore, consistent with our observational results, recruiters also believe that this gap is not due to negotiation behavior; in columns 3 and 4, the salary gap remains a precise 0 and the non-salary compensation gender gap decreases slightly (though not distinguishably from the pre-negotiation gap) to 3.7%. These gender gaps are also demonstrated visually in Figure A4, where the distributions of non-salary and total compensation are shifted left for women relative to men, and the distributions of salary for women and men are similar.

Do recruiters believe the gender gap is driven by women being less likely to negotiate or, conditional on negotiation, worse at it? Contrary to these explanations, we find that recruiters also predict no gender differences in negotiation or job search behavior. In Table 6, we report results from an OLS regression of recruiter predictions for negotiation behavior, the number of offers received, and tenure controlling for recruiter, resume, and resume order fixed effects.<sup>14</sup> In columns 1 and 2, recruiters believe that women are no less likely to attempt to negotiate either compensation or non-compensation in their offer packages. On the intensive margin of negotiation, recruiters believe that women are as skilled at negotiation as men, since the non-salary gap remains constant or, if anything, slightly declines post-negotiation (Table 5). Thus, it is unlikely that the gender gap is driven by differences in perceived propensity to negotiate or perceived returns to negotiation.

Another potential explanation for the predicted gender earnings gap is that firms be-

---

<sup>14</sup>This variable is coded as an indicator, where the dependent variable is equal to 1 if the recruiter thinks the candidate is “extremely likely to have negotiated.” While this is the highest point on the Likert scale used for this answer, recruiters think that over half of the candidates are extremely likely to have negotiated their compensation.

lieve that women have fewer outside offers and are thus less elastic to lower initial offers (Robinson, 1969). In column 3 of Table 6, we show that this is not the case—recruiters believe there is no gender difference in the number of offers received. A related explanation is that despite receiving the same number of offers, women receive offers from lower-paying industries. For example, a finance firm might lowball women compared to men who have the same number of offers if they think that women’s outside offers come from lower-paying non-finance firms and men’s outside offers come from other comparable finance firms. However, we see that recruiters do not believe that men and women’s outside offers come from different industries (Table A4). Indeed, recruiters believe that men and women are equally as likely to receive offers across several industries (consulting, tech, finance, pharma, retail, automotive/aerospace, energy).<sup>15</sup> Thus, it is unlikely that the gender gap can be explained by firms’ beliefs about the difference in number or type of outside offers received by women and men.

We also explore whether firms believe that women have shorter tenure at the firm and therefore offer women lower compensation. If firms believe that women will leave the firm quickly (whether to switch firms, take maternity leave, or exit the labor market), they may be less interested in attracting them to the firm. However, recruiters actually believe that women on average stay at the firm for 0.4 more months than men (Table 6). If anything, this would mean that firms should offer women higher compensation packages to create a workforce with lower turnover. Therefore it is unlikely that firms are offering women lower compensation packages due to beliefs about shorter tenure.

## VI External validity and long-term implications

Our findings using MIT student data suggest that even among male and female MIT students who accept a job offer for the same position at the same firm, a gender earnings gap persists. Moreover, we find that this gap is explained entirely by firms lowballing women in their initial non-salary offers. Do similar patterns hold in the broader labor market? We use data from Levels.fyi to test whether these patterns emerge in a national sample of newly hired workers for high-skill jobs in industries such as tech, finance, and consulting. We estimate within employer-occupation-location gender earnings gaps among newly hired workers separately by years of experience using a regression specification akin to that of Equation (1). Table 7 reports our estimates separately for individuals with 0 years of prior

---

<sup>15</sup>While the predictions for industry could not be incentivized, the recruiters’ responses suggest thoughtfulness when answering: the predicted industries of offers resemble the distribution of resumes designed. Most common industries chosen are finance, consulting, and tech, whereas recruiters believe that fewer than 7% of candidates received offers from the automotive/aerospace industry.

experience, 2-5 years of prior experience, and 6-10 years of prior experience.

Column (1) in Table 7 shows that among newly hired workers starting at the same role, the gender gap in base salary is a precise 0. However, even among these workers, a statistically significant gap in non-salary components of compensation emerges in column (2), with a 4% gap in equity and signing bonus. This gap confirms the broad existence of a within-occupation gender gap in non-salary components of compensation. Additionally, while the gap is smaller than the gap we observe in our MIT data, it matches the gap perceived by the recruiters in our experiment (Table 5). Turning to columns (3)-(7), another notable fact emerges: the gap widens among more experienced workers. We observe a 2-3% gap in base salary among workers with several years of experience, and the non-salary gap grows to 6% among workers with 2-5 years of experience and up to 8% among workers with 6-10 years of prior experience. Because we focus on newly hired workers, these bonuses cannot be explained by differences in performance or productivity at the firm from which they received the offer.

Next, we show that bonus and equity become an increasingly large fraction of overall compensation among these workers over time. Figure A5 shows that while bonus and equity comprise just under 20% of total compensation for newly hired workers with less than 1 year of prior experience, this amount grows steadily to exceed 40% of total income for workers with over 18 years of experience. This suggests that even if the early-career gender gap in bonus and equity may seem small, this gap may compound over time as these components become more substantial. For example, a woman with over six years of working experience receives an 8.8% lower bonus than an observably identical man on a mean bonus of \$115,700. This translates to over \$10,000 lost due to gender alone. This also underscores the importance of accounting for non-salary components of compensation such as signing bonuses and equity in studies of the gender earnings gap.

## VII Conclusion

By focusing on within employer-occupation gender earnings gaps among newly hired MIT graduates, we provide evidence that gender pay disparities can arise even in the absence of gender differences in negotiation, job search, sorting, and on-the-job productivity. We find a 3% gender gap in total compensation that is driven entirely by non-salary components such as signing bonus and equity, with no difference in base salary. Moreover, this gap emerges at the initial offer stage *prior* to negotiation and remains constant across pre- and post-negotiation offers. Motivated by these patterns, we develop a simple model in which even a small number of discriminatory firms induce market-wide underpayment of women,

as firms exploit anticipated differences in outside offers resulting from other discriminatory firms. This yields an equilibrium in which *all firms*, including those without discriminatory preferences, perpetuate gender disparities. We provide direct evidence of this mechanism in an incentivized resume evaluation experiment, finding that recruiters predict lower non-salary offers for women. These same recruiters, however, predict no differences in job search effort, negotiation behavior, or number of outside offers. We also extend our analysis beyond MIT students by examining newly hired high-skill workers across tech, finance, and consulting sectors using data from Levels.fyi. We find qualitatively similar patterns: base salary gaps are near zero for entry-level hires, but gender gaps in bonuses and equity remain statistically significant. Furthermore, gaps in non-salary compensation observed in the Levels.fyi data widen with experience, both in dollar terms and as a share of total compensation.

Over the past decade, a growing number of states have passed laws aimed at reducing gender earnings gaps, particularly through regulations on pay transparency and salary history inquiries. In 2016, Massachusetts became the first state to ban employers from inquiring about a candidate’s salary history, aiming to prevent past pay disparities from influencing future compensation decisions. Since 2020, salary transparency laws mandating employers to include salary ranges in job postings have also passed in several major states including Colorado, New York, California, Maryland, Washington, and Illinois. While these legislative efforts have gained traction, they overlook key elements of compensation—such as bonuses and equity—where we find persistent and significant gender gaps. Our findings suggest that research and policy focused solely on base salary may understate the true extent of gender disparities, especially in high-skill labor markets. Non-salary components not only drive much of the observed disparities but also grow in importance over time, accounting for more than 40% of total compensation among experienced workers. This implies that early differences in non-salary components may worsen over the course of a woman’s career, exacerbating lifetime earnings gaps.

While much recent work has focused on improving women’s outcomes through interventions and legislations targeting worker decisions, our results indicate that such interventions may be insufficient when employers drive disparities from the outset. We consider a setting where even when women negotiate as frequently and successfully as men, they begin from a lower baseline offer. Our model illustrates how small pockets of discrimination can have market-wide effects in equilibrium, even in markets characterized by otherwise fair-minded firms. Under these circumstances, even perfect parity in worker-side behavior cannot eliminate a gap originating in initial firm decisions. Interventions focused exclusively on improving worker behavior—such as negotiation training or information provision—are unlikely to fully eliminate gender disparities. Addressing the gender earnings gap will therefore likely require

greater attention on firm behavior. Future work could explore whether interventions that directly target a firm's beliefs and practices could mitigate discrimination. Understanding the extent to which wage-setting behavior is shaped by perceptions of other firms' behavior may be key to closing persistent gender gaps in earnings.

## Tables and Figures

Table 1: Summary statistics of main sample by gender and degree type

	Undergraduate		MBA	
	<i>Female</i>	<i>Male</i>	<i>Female</i>	<i>Male</i>
<b>Accepted Offer Characteristics</b>				
Base Salary	\$104,981	\$106,925	\$168,305	\$170,398
Total Compensation	\$132,107	\$138,834	\$226,552	\$238,938
Decision Deadline (weeks)	6	7	10	10
<b>Negotiation and Job Search</b>				
Negotiated Salary	0.15	0.15	0.15	0.14
Negotiated Bonus	0.15	0.13	0.18	0.17
# Applications	12.14	9.83	8.01	10.16
# Offers	2.11	1.96	2.07	2.25
Search Duration (months)	2.90	3.20	2.37	2.82
<b>Demographics</b>				
Hispanic	0.10	0.21	0.03	0.07
Black	0.03	0.10	0.03	0.02
Asian	0.34	0.16	0.19	0.10
International	0.05	0.08	0.28	0.34
<b>N</b>	467	486	260	444

NOTE.— This table reports summary statistics for our final analysis sample for undergraduates and MBA students in the GSS dataset. Earnings are CPI adjusted to 2022 dollars and winsorized at 1 percent above and below. The sample is restricted to MBA and undergraduate students in the GSS who were actively seeking full-time jobs between academic years 2010-2024 and received job offers in the US from firms that hired three or more students per year.



Table 2: Within employer-occupation gender gaps in final total compensation

	Total Comp.	Base Salary	Bonus + Equity	Total Comp.	Base Salary	Bonus + Equity
<i>Female</i>	-0.031*** (0.010)	-0.005 (0.003)	-0.102*** (0.035)	-0.034*** (0.012)	-0.003 (0.004)	-0.116*** (0.041)
<i>Returning to Internship</i>				-0.001 (0.013)	-0.008* (0.004)	0.012 (0.044)
<i>Negotiated Bonus or Equity</i>				0.073*** (0.023)	0.018*** (0.007)	0.180*** (0.066)
<i>Negotiated Salary</i>				-0.022 (0.018)	-0.005 (0.006)	-0.035 (0.052)
<i>Has Outside Offer</i>				0.039 (0.026)	0.005 (0.007)	0.114 (0.076)
Observations	2,428	2,428	2,405	1,517	1,517	1,508
Unique Employers	222	222	212	145	145	141
Mean Outcome	\$216,448	\$159,238	\$57,756	\$225,182	\$162,141	\$63,417

NOTE.— This table reports results from a Poisson regression of total compensation and compensation subcomponents on an indicator for the candidate being female. Earnings are CPI adjusted to 2022 dollars and winsorized at 1 percent above and below. Robust standard errors are reported in parentheses. All regressions include fixed effects for year as well as full interactions of employer-occupation-location. The sample is restricted to Sloan MBA students who were actively seeking full-time jobs between academic years 2010-2024 and received job offers in the US. The sample in columns 4-6 is restricted to students seeking full-time jobs between academic years 2014-2024 due to data on outside offers beginning in 2014.

Table 3: Within employer-occupation gender gaps in pre- and post-negotiated compensation

	Pre-Negotiation		Post-Negotiation	
	<i>Salary</i>	<i>Non-Salary</i>	<i>Salary</i>	<i>Non-Salary</i>
<i>Female</i>	-0.004 (0.007)	-0.155*** (0.052)	-0.005 (0.008)	-0.145*** (0.051)
Observations	1,272	1,263	1,272	1,266
Unique Employers	61	58	61	59
Mean Outcome	\$134,655	\$44,251	\$135,586	\$46,004

NOTE.— This table reports results from a Poisson regression of total compensation and base salary both pre- and post-negotiation on an indicator for the candidate being female. Earnings are CPI adjusted to 2022 dollars and winsorized at 1 percent above and below. Robust standard errors are reported in parentheses. All regressions include fixed effects for year as well as full interactions of employer-location-degree and major fixed effects. The sample is restricted to MBA and undergraduate students in the GSS who were actively seeking full-time jobs between academic years 2010-2024 and received job offers in the US.

Table 4: Within employer-occupation gender gaps in negotiation and job search

	Negotiated Salary	Negotiated Non-Salary	% Gain from Negotiation	# Applications	# Offers	Search Period (months)	Decision Deadline (weeks)
<i>Female</i>	-0.000 (0.019)	0.002 (0.019)	0.400 (0.266)	-0.252 (1.050)	0.002 (0.083)	-0.273** (0.132)	-0.086 (0.377)
Observations	1,315	1,315	1,272	698	1,125	945	1,311
$R^2$	0.241	0.319	0.195	0.230	0.204	0.348	0.317
Unique Employers	62	62	61	56	62	53	62
Mean Outcome	0.14	0.15	1.21	10.08	2.10	2.87	7.98

NOTE.— This table reports results from an OLS regression of whether or not a student negotiated their salary or bonus, the % increase in total compensation as a result of negotiation, job search duration, the number of applications and offers, and how long they had to accept the offer on an indicator for the candidate being female. Robust standard errors are reported in parentheses. All regressions include fixed effects for year as well as full interactions of employer-location-degree and major fixed effects. The sample is restricted to MBA and undergraduate students in the GSS who were actively seeking full-time jobs between academic years 2010-2024 and received job offers in the US. Some outcomes are missing for a subset of years due to changes in the GSS questionnaire: the number of applications was not collected in years 2015, 2016, 2018, 2020, 2021, the number of outside offers was not collected in years 2020 and 2021.

Table 5: Recruiters' predicted pre- and post-negotiation compensation components

	Pre-Negotiation		Post-Negotiation	
	<i>Salary</i>	<i>Non-Salary</i>	<i>Salary</i>	<i>Non-Salary</i>
<i>Female Resume</i>	-0.004 (0.007)	-0.046*** (0.015)	-0.000 (0.007)	-0.037** (0.014)
Observations	4,800	4,800	4,800	4,800
Unique Recruiters	480	480	480	480
Mean Outcome	\$146,338	\$54,605	\$155,581	\$60,217

NOTE.— This table reports results from a Poisson regression of predicted base salary and non-salary amounts in dollars on an indicator for the candidate being female. Predicted earnings are winsorized at 5 percent above and below. Robust standard errors are reported in parentheses and clustered at the recruiter level. All regressions include fixed effects for resume, resume order, recruiter, and recruiter demographics (i.e., race, gender).

Table 6: Predicted negotiation behavior, outside offers, and tenure in resume evaluation experiment

	Negotiated Comp.	Negotiated Non-Comp.	Number of Offers	Tenure (Months)
<i>Female Resume</i>	-0.004 (0.011)	0.007 (0.011)	-0.030 (0.047)	0.410** (0.199)
Observations	4,800	4,800	4,800	4,800
$R^2$	0.555	0.512	0.650	0.497
Unique Recruiters	480	480	480	480
Mean Outcome	0.57	0.35	5.72	23.34

NOTE.— This table reports results from an OLS regression of recruiter predictions of whether or not a candidate negotiated their offer, how many offers the candidate received, and the number of months that the candidate stayed at their firm on an indicator for the candidate being female. All regressions include fixed effects for resume, resume order, and recruiter. Standard errors are clustered at the recruiter level.

Table 7: Within employer-occupation gender earnings gap among new hires in Levels.fyi

	0 yrs experience		2-5 yrs experience		6-10 yrs experience	
	<i>Salary</i>	<i>Equity + Bonus</i>	<i>Salary</i>	<i>Equity + Bonus</i>	<i>Salary</i>	<i>Equity + Bonus</i>
<i>Female</i>	-0.001 (0.003)	-0.041*** (0.014)	-0.021*** (0.003)	-0.058*** (0.015)	-0.032*** (0.005)	-0.088*** (0.020)
Observations	7,369	7,125	8,759	8,520	4,330	4,214
Unique Employers	403	348	501	425	303	274
Mean Outcome	\$124,491	\$41,727	\$156,898	\$72,440	\$185,943	\$115,687

NOTE.— This table reports results from a Poisson regression of predicted base salary and non-salary amounts in dollars on an indicator for the candidate being female among newly hired workers in the Levels.fyi data. Regressions include fully saturated fixed effects for company, location, and role as well as fixed effects for the year during which the candidate received the offer. Robust standard errors are reported in parentheses.

# Appendix

## A Appendix Tables & Figures

Table A1: Within employer-occupation gender gaps in final total compensation

	Total Comp.	Base Salary	Bonus + Equity
<i>Female</i>	-0.029*** (0.010)	-0.006* (0.003)	-0.094*** (0.035)
<i>Black</i>	-0.057*** (0.017)	-0.008 (0.007)	-0.206*** (0.065)
<i>Asian</i>	-0.021* (0.012)	0.004 (0.004)	-0.094** (0.041)
<i>Hispanic</i>	-0.061** (0.027)	-0.005 (0.009)	-0.252** (0.117)
<i>International</i>	-0.055*** (0.015)	-0.001 (0.005)	-0.201*** (0.050)
Observations	2,302	2,302	2,281
Unique Employers	214	214	205
Mean Outcome	\$217,040	\$159,498	\$58,072

NOTE.— This table reports results from a Poisson regression of total compensation and compensation subcomponents on indicators for the candidate being female, Black, Asian, Hispanic, or international. Indicators for Native Hawaiian or Pacific Islander and American Indian or Native Alaskan are also included in the regression but not reported in this table due to small sample sizes in these racial groups. Earnings are CPI adjusted to 2022 dollars and winsorized at 1 percent above and below. Robust standard errors are reported in parentheses. All regressions include fixed effects for year as well as full interactions of employer-occupation-location. The sample is restricted to Sloan MBA students who were actively seeking full-time jobs between academic years 2010-2024 and received job offers in the US.

Table A2: Within employer-occupation gender earnings gaps by whether firms ask for a desired compensation range

	Asked Expected Comp. Range		No Expected Comp. Range	
	<i>Salary</i>	<i>Total Comp.</i>	<i>Salary</i>	<i>Total Comp.</i>
<i>Female</i>	0.026 (0.032)	-0.073** (0.051)	-0.008 (0.007)	-0.039** (0.015)
Observations	280	278	992	989
Unique Employers	10	10	51	51
Mean Outcome	\$105,557	\$138,545	\$142,868	\$191,325

NOTE.— This table reports results from a Poisson regression of pre-negotiation total compensation and base salary on an indicator for the candidate being female, separately by firms that asked for expected compensation ranges and firms that did not. Earnings are CPI adjusted to 2022 dollars and winsorized at 1 percent above and below. Robust standard errors are reported in parentheses. All regressions include fixed effects for year as well as full interactions of employer-location-degree and major fixed effects. The sample is restricted to MBA and undergraduate students in the GSS who were actively seeking full-time jobs between academic years 2010-2024 and received job offers in the US.

Table A3: Recruiters in resume evaluation experiment

	Mean	SD
<b>Current Employment</b>		
Employed Full-Time	0.92	0.27
Works at Private For-Profit Firm	0.80	0.40
Firm Size	416.45	373.67
Works at Fortune 500	0.40	0.49
<b>Hiring Experience</b>		
People Hired in Past Year	5.64	3.44
Currently Hiring	0.94	0.23
Mostly Hires MBAs	0.52	0.50
<b>Demographics</b>		
Female	0.41	0.49
White	0.62	0.49
Black	0.32	0.47
Asian	0.04	0.20
Politically Conservative	0.56	0.50
N	480	-

NOTE.—This table reports summary statistics of the 480 recruiters on Prolific who participated in our incentivized resume evaluation experiment. Our sample is restricted to recruiters who are US-based and have experience hiring MBA graduates.



Table A4: Predicted industries of outside offers in resume evaluation experiment

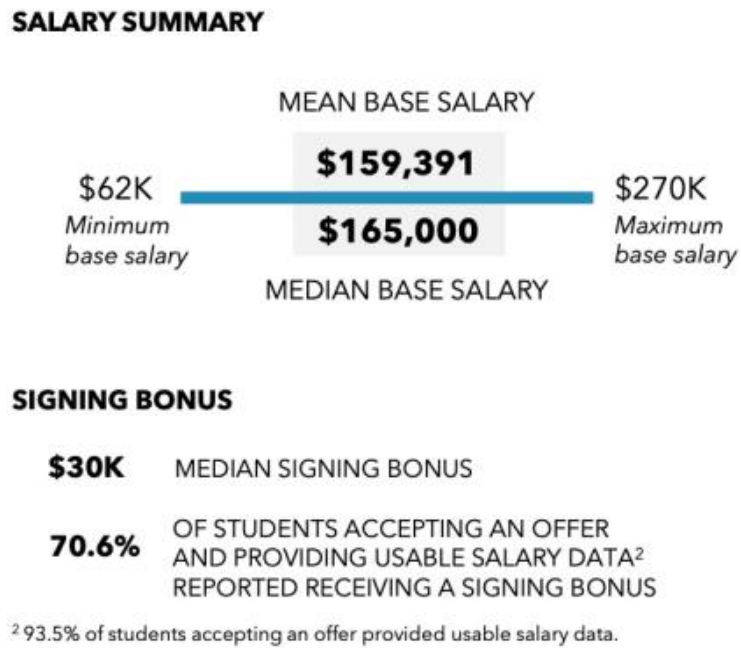
	Consulting	Tech	Finance	Pharma	Retail	Auto/Aero	Energy	Other
<i>Female Resume</i>	-0.005 (0.013)	-0.014 (0.013)	-0.015 (0.013)	0.003 (0.008)	0.011 (0.010)	0.004 (0.007)	0.001 (0.007)	0.004 (0.004)
Observations	4,800	4,800	4,800	4,800	4,800	4,800	4,800	4,800
Unique Recruiters	480	480	480	480	480	480	480	480
Mean Outcome	0.479	0.436	0.528	0.129	0.175	0.0683	0.0746	0.0219

NOTE.— This table reports results from an OLS regression of recruiter predictions of whether or not a candidate received an offer from a particular industry on an indicator for the candidate being female. All regressions include fixed effects for resume, resume order, and recruiter. Standard errors are clustered at the recruiter level. The predicted industry distribution sums to more than 1 (or 100%) because recruiters are permitted to select more than one industry for a particular resume.

41

NOTE.— Interface for the annual Sloan MBA Employment survey. Students are asked location and compensation details about the offer they accepted as well as their negotiation process.

Figure A2: Infographic provided to participants in resume evaluation experiment



NOTE.— Infographic from MIT Sloan brochure on base salary and signing bonus among Sloan MBA graduates in 2022.

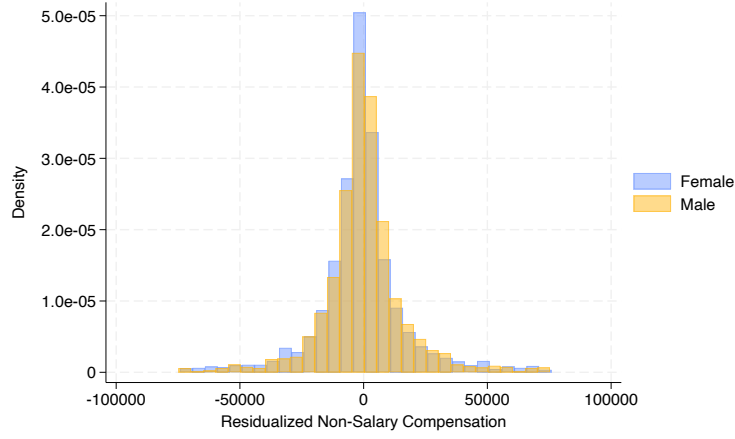
Figure A3: Sample resumes used in audit experiment

<b>GLORIA CARRASCO</b> (617) 555-9876   <a href="mailto:gloria_carrasco@mit.edu">gloria_carrasco@mit.edu</a>	
<b>EDUCATION</b>	
<b>MIT SLOAN SCHOOL OF MANAGEMENT</b> <i>Candidate for MBA, May 2024</i>	Cambridge, MA 2022 - 2024
<ul style="list-style-type: none"><li>• Pursuing Business Analytics Certificate and Finance track</li><li>• Director of Class Visit Program, Core Fellow, Co-president of FinTech Club</li></ul>	
<b>INSTITUTO TECNOLÓGICO DE BUENOS AIRES (ITBA)</b> <i>BS Industrial Engineering</i>	Buenos Aires, Argentina 2013-2017
<ul style="list-style-type: none"><li>• Study Abroad at ESCP EUROPE Paris, France (Spring and Summer 2015)</li><li>• First prize at Intel Ideation Workshop, I.T.B.A (48hs Design thinking competition)</li><li>• TA - Production organization I, Managing +30 student classes</li></ul>	
<b>EXPERIENCE</b>	
<b>TIKTOK</b> <i>App Product Quality Intern, Customer Operations</i>	Remote, Los Angeles, USA Summer 2023
<ul style="list-style-type: none"><li>• Design, build and implement tool and process for Automatic Voice of Customer reports to reduce monthly time spent on reporting from 160hs to 20hs. Focus on user research, change management and team training.</li></ul>	
<b>VISA, CONSULTING AND ANALYTICS</b> <i>Consultant (promoted from Associate Analyst in 2021)</i>	Buenos Aires, Argentina 2019 - 2022
<ul style="list-style-type: none"><li>• Led business analysis and design of operational models for 7 projects advising leading financial institutions in market entry for payment acquisition services. Interfaced with key internal and external stakeholders, including commercial, operations, IT, planning and legal areas, throughout the entire project lifecycle</li><li>• Special recognition: Reached Latin America final stage at internal Olympics competition</li><li>• Designed a new credit card product based on market opportunity, clients' needs assessment and P&amp;L analysis for leading bank in Brazil, creating revenue opportunity for \$US 40 MM/year</li><li>• Proposed initiatives to increase conversion rate by +20% and decrease delivery time from an average of 6 weeks to less than 2 weeks for a leading Provincial Bank. Directed gap analysis in online acquisition of new credit card clients</li><li>• Formulated migration strategy and plan for 280k credit card portfolio for one of top issuers of credit cards in Argentina</li><li>• Conducted onboarding process and coaching for 6 new analysts in the team</li><li>• Launched Argentinean chapter of YoPros Argentina, a resource group within Visa to promote inclusion and development of young professionals, corporate social responsibility and team building. Coordinated 8 events for entire office</li></ul>	
<b>GLOBANT</b> Customized software for financial institutions, retail industry and consumer goods <i>Business Analyst (promoted from intern in 2018)</i>	Buenos Aires, Argentina 2017 - 2019
<ul style="list-style-type: none"><li>• Led design of software for order tracing and schedule programming of sole factory with a production of IMM soles per year</li><li>• Designed, set-up and analyzed KPI dashboards for 5 clients in different industries including: National Transportation Ministry of Argentina – tracking of Construction public works; World's largest beverage company - Point of sale smart gondolas data; Transportation company - Operational data; Financial portfolio manager - Client portfolio tracking</li><li>• Oversaw analysis for cost and time-to-market reduction through a re-engineering of supply chain process, software and information systems for a leading Argentine shoe retailer</li><li>• Coordinated 3 suppliers to achieve prototype for Samsung Safety truck (solution designed to reduce accidents in overtake maneuvers). Featured in several publications: Fortune, BBC, Engaget, Verge and Time Magazine</li></ul>	
<b>ADDITIONAL INFORMATION</b>	
<ul style="list-style-type: none"><li>• Languages: Native Spanish, Portuguese, and conversational in French</li><li>• Promoter of Education in Argentina through several NGO: San Felipe, Integrar, Los Toritos</li><li>• Sports: Soccer, running, cycling and ski (especially powder days!)</li><li>• Other studies: 2018 - Cambridge Judge Business School –Alternative Finance in Digitised economy; Strategyzer – Master</li><li>• Business model canvas and Value propositions. Extensive user of Coursera (8 online courses)</li></ul>	

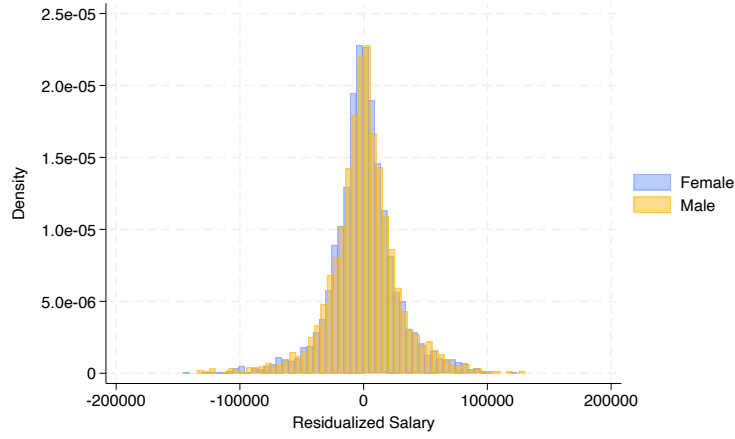
<b>JULIO CARRASCO</b> (617) 555-9876   <a href="mailto:julio_carrasco@mit.edu">julio_carrasco@mit.edu</a>	
<b>EDUCATION</b>	
<b>MIT SLOAN SCHOOL OF MANAGEMENT</b> <i>Candidate for MBA, May 2024</i>	Cambridge, MA 2022 - 2024
<ul style="list-style-type: none"><li>• Pursuing Business Analytics Certificate and Finance track</li><li>• Director of Class Visit Program, Core Fellow, Co-president of FinTech Club</li></ul>	
<b>INSTITUTO TECNOLÓGICO DE BUENOS AIRES (ITBA)</b> <i>BS Industrial Engineering</i>	Buenos Aires, Argentina 2013-2017
<ul style="list-style-type: none"><li>• Study Abroad at ESCP EUROPE Paris, France (Spring and Summer 2015)</li><li>• First prize at Intel Ideation Workshop, I.T.B.A (48hs Design thinking competition)</li><li>• TA - Production organization I, Managing +30 student classes</li></ul>	
<b>EXPERIENCE</b>	
<b>TIKTOK</b> <i>App Product Quality Intern, Customer Operations</i>	Remote, Los Angeles, USA Summer 2023
<ul style="list-style-type: none"><li>• Design, build and implement tool and process for Automatic Voice of Customer reports to reduce monthly time spent on reporting from 160hs to 20hs. Focus on user research, change management and team training.</li></ul>	
<b>VISA, CONSULTING AND ANALYTICS</b> <i>Consultant (promoted from Associate Analyst in 2021)</i>	Buenos Aires, Argentina 2019 - 2022
<ul style="list-style-type: none"><li>• Led business analysis and design of operational models for 7 projects advising leading financial institutions in market entry for payment acquisition services. Interfaced with key internal and external stakeholders, including commercial, operations, IT, planning and legal areas, throughout the entire project lifecycle</li><li>• Special recognition: Reached Latin America final stage at internal Olympics competition</li><li>• Designed a new credit card product based on market opportunity, clients' needs assessment and P&amp;L analysis for leading bank in Brazil, creating revenue opportunity for \$US 40 MM/year</li><li>• Proposed initiatives to increase conversion rate by +20% and decrease delivery time from an average of 6 weeks to less than 2 weeks for a leading Provincial Bank. Directed gap analysis in online acquisition of new credit card clients</li><li>• Formulated migration strategy and plan for 280k credit card portfolio for one of top issuers of credit cards in Argentina</li><li>• Conducted onboarding process and coaching for 6 new analysts in the team</li><li>• Launched Argentinean chapter of YoPros Argentina, a resource group within Visa to promote inclusion and development of young professionals, corporate social responsibility and team building. Coordinated 8 events for entire office</li></ul>	
<b>GLOBANT</b> Customized software for financial institutions, retail industry and consumer goods <i>Business Analyst (promoted from intern in 2018)</i>	Buenos Aires, Argentina 2017 - 2019
<ul style="list-style-type: none"><li>• Led design of software for order tracing and schedule programming of sole factory with a production of IMM soles per year</li><li>• Designed, set-up and analyzed KPI dashboards for 5 clients in different industries including: National Transportation Ministry of Argentina – tracking of Construction public works; World's largest beverage company - Point of sale smart gondolas data; Transportation company - Operational data; Financial portfolio manager - Client portfolio tracking</li><li>• Oversaw analysis for cost and time-to-market reduction through a re-engineering of supply chain process, software and information systems for a leading Argentine shoe retailer</li><li>• Coordinated 3 suppliers to achieve prototype for Samsung Safety truck (solution designed to reduce accidents in overtake maneuvers). Featured in several publications: Fortune, BBC, Engaget, Verge and Time Magazine</li></ul>	
<b>ADDITIONAL INFORMATION</b>	
<ul style="list-style-type: none"><li>• Languages: Native Spanish, Portuguese, and conversational in French</li><li>• Promoter of Education in Argentina through several NGO: San Felipe, Integrar, Los Toritos</li><li>• Sports: Soccer, running, cycling and ski (especially powder days!)</li><li>• Other studies: 2018 - Cambridge Judge Business School –Alternative Finance in Digitised economy; Strategyzer – Master</li><li>• Business model canvas and Value propositions. Extensive user of Coursera (8 online courses)</li></ul>	

NOTE.— Recruiters are asked to predict job search behavior using the resumes of ten recent MBA candidates at MIT Sloan School of Management. Resumes used in the audit experiment are designed using real MIT Sloan MBA resumes. Each of the ten unique resumes is randomized to show either a male or female name at the top.

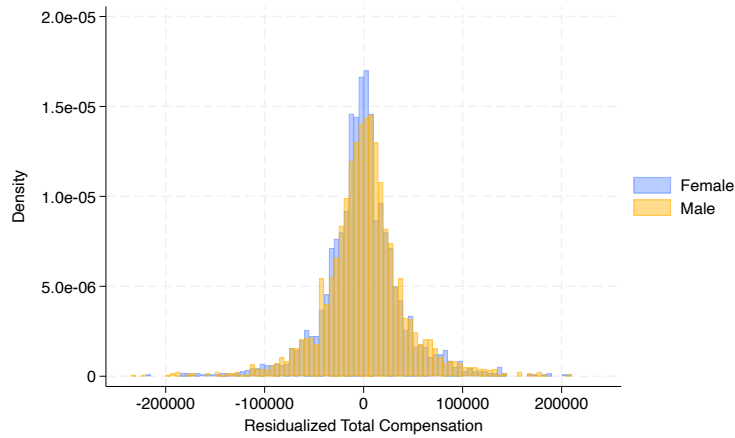
Figure A4: Distribution of residualized compensation by gender



(a) Predicted non-salary compensation



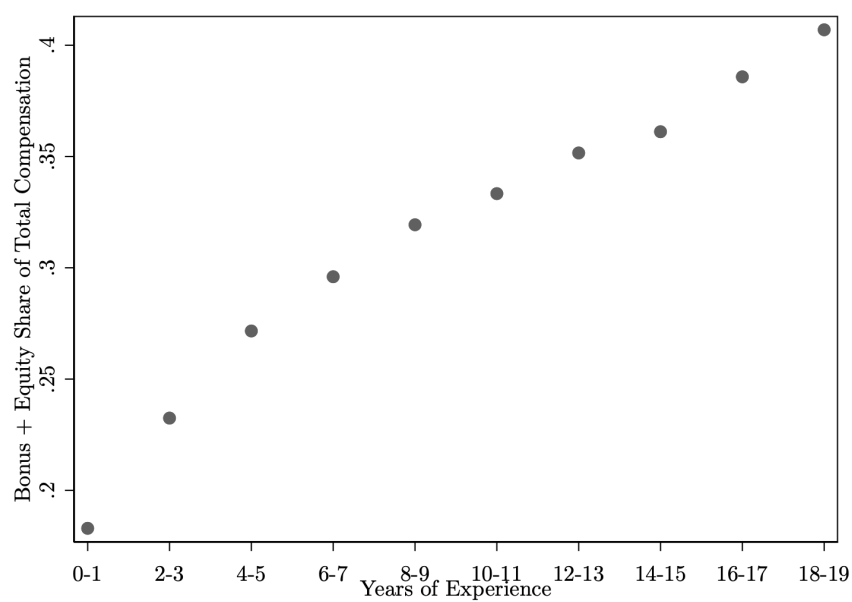
(b) Predicted salary compensation



(c) Predicted total compensation

NOTE.— Histograms of non-salary, salary, and total compensation predicted by recruiters for men and women. Compensation is winsorized at 5th and 95th percentiles.

Figure A5: Share of total compensation that is either bonus or equity by years of experience



NOTE.— Average share of total compensation represented by the sum of signing bonuses and equity among newly hired workers by years of experience. Data are restricted to job offers for workers who were newly hired in the Levels.fyi dataset between 2018-2013.

## B Analyses using OLS

Table B1: Within employer-occupation gender gaps in final total compensation, OLS

	Log Total Comp.	Log Salary	Bonus + Equity	Log Total Comp.	Log Salary	Bonus + Equity
<i>Female</i>	-0.033*** (0.010)	-0.006 (0.004)	-6,159.907*** (2,223.278)	-0.035*** (0.012)	-0.003 (0.004)	-7,297.950** (2,943.001)
<i>Returning to Internship</i>				-0.002 (0.014)	-0.009* (0.005)	1,249.358 (3,303.867)
<i>Negotiated Bonus or Equity</i>				0.071*** (0.022)	0.018** (0.008)	14,369.285** (5,870.607)
<i>Negotiated Salary</i>				-0.025 (0.018)	-0.007 (0.006)	-4,822.038 (4,547.537)
<i>Has Outside Offer</i>				0.045* (0.024)	0.005 (0.008)	8,381.784 (6,487.107)
Observations	2,428	2,428	2,428	1,517	1,517	1,517
Unique Employers	222	222	222	145	145	145
Mean Outcome (in \$)	\$216,447	\$159,238	\$57,209	\$225,182	\$162,141	\$63,040

NOTE.— This table reports results from an OLS regression of total compensation and compensation subcomponents on an indicator for the candidate being female. Earnings are CPI adjusted to 2022 dollars and winsorized at 1 percent above and below. Robust standard errors are reported in parentheses. All regressions include fixed effects for year as well as full interactions of employer-occupation-location. The sample is restricted to Sloan MBA students who were actively seeking full-time jobs between academic years 2010-2024 and received job offers in the US. The sample in columns 4-6 is restricted to students seeking full-time jobs between academic years 2014-2024 due to data on outside offers beginning in 2014.

Table B2: Within employer-occupation gender gaps in pre- and post-negotiated compensation, OLS

	Pre-Negotiation		Post-Negotiation	
	<i>Log Salary</i>	<i>Non-Salary</i>	<i>Log Salary</i>	<i>Non-Salary</i>
<i>Female</i>	-0.002 (0.009)	-6,644.437*** (2,346.886)	-0.000 (0.009)	-6,515.669*** (2,424.939)
Observations	1,272	1,273	1,272	1,273
Unique Employers	61	61	61	61
Mean Outcome (in \$)	\$134,655	\$43,903	\$135,586	\$45,751

NOTE.— This table reports results from an OLS regression of base salary and non-salary compensation both pre- and post-negotiation on an indicator for the candidate being female. Earnings are CPI adjusted to 2022 dollars and winsorized at 1 percent above and below. Robust standard errors are reported in parentheses. All regressions include fixed effects for year as well as full interactions of employer-location-degree and major fixed effects. The sample is restricted to MBA and undergraduate students in the GSS who were actively seeking full-time jobs between academic years 2010-2024 and received job offers in the US.



Table B3: Recruiters' predicted pre- and post-negotiation compensation components, OLS

	Pre-Negotiation		Post-Negotiation	
	<i>Log Salary</i>	<i>Log Non-Salary</i>	<i>Log Salary</i>	<i>Log Non-Salary</i>
<i>Female Resume</i>	-0.005 (0.008)	-0.050*** (0.018)	0.002 (0.009)	-0.041** (0.018)
Observations	4,800	4,800	4,800	4,800
Unique Recruiters	480	480	480	480
Mean Outcome (in \$)	\$146,338	\$54,605	\$155,581	\$60,217

NOTE.— This table reports results from an OLS regression of predicted base salary and non-salary amounts in log dollars on an indicator for the candidate being female. Predicted earnings are winsorized at 5 percent above and below and logged after. Robust standard errors are reported in parentheses and clustered at the recruiter level. All regressions include fixed effects for resume, resume order, recruiter, and recruiter demographics (i.e., race, gender).

## C Within employer-occupation gender gaps with controls

Table C1: Within employer-occupation gender gaps in pre- and post-negotiated compensation

	Pre-Negotiation		Post-Negotiation	
	<i>Salary</i>	<i>Non-Salary</i>	<i>Salary</i>	<i>Non-Salary</i>
<i>Female</i>	-0.009 (0.008)	-0.175*** (0.058)	-0.011 (0.008)	-0.164*** (0.057)
Observations	1,115	1,106	1,115	1,109
GPA Controls	Y	Y	Y	Y
Race FE	Y	Y	Y	Y
Unique Employers	58	55	58	56
Mean Outcome	\$133,312	\$44,309	\$134,245	\$46,032

NOTE.— This table reports results from a Poisson regression of total compensation and base salary both pre- and post-negotiation on an indicator for the candidate being female. Earnings are CPI adjusted to 2022 dollars and winsorized at 1 percent above and below. Robust standard errors are reported in parentheses. All regressions include fixed effects for year as well as full interactions of employer-location-degree and major fixed effects. All regressions also include controls for GPA and race fixed effects. The sample is restricted to MBA and undergraduate students in the GSS who were actively seeking full-time jobs between academic years 2010-2024 and received job offers in the US.

Table C2: Within employer-occupation gender gaps in negotiation and job search

	Negotiated Salary	Negotiated Non-Salary	% Gain from Negotiation	# Applications	# Offers	Search Period (months)	Decision Deadline (weeks)
<i>Female</i>	-0.001 (0.022)	-0.004 (0.022)	0.319 (0.334)	-1.028 (1.190)	-0.027 (0.099)	-0.225 (0.146)	-0.216 (0.415)
Observations	1,152	1,152	1,115	579	971	852	1,153
GPA Controls	Y	Y	Y	Y	Y	Y	Y
Race FE	Y	Y	Y	Y	Y	Y	Y
Unique Employers	58	58	58	51	57	50	59
Mean Outcome	0.14	0.15	1.30	10.65	2.13	2.89	7.87

NOTE.— This table reports results from an OLS regression of whether or not a student negotiated their salary or bonus, the % increase in total compensation as a result of negotiation, job search duration, the number of applications and offers, and how long they had to accept the offer on an indicator for the candidate being female. Robust standard errors are reported in parentheses. All regressions include fixed effects for year as well as full interactions of employer-location-degree and major fixed effects. All regressions also include controls for GPA and race fixed effects. The sample is restricted to MBA and undergraduate students in the GSS who were actively seeking full-time jobs between academic years 2010-2024 and received job offers in the US. Some outcomes are missing for a subset of years due to changes in the GSS questionnaire: the number of applications was not collected in years 2015, 2016, 2018, 2020, 2021, the number of outside offers was not collected in years 2020 and 2021.

## References

- Agan, Amanda, Bo Cowgill, and Laura Katherine Gee**, “Do Workers Comply with Salary History Bans? A Survey on Voluntary Disclosure, Adverse Selection, and Unraveling,” *AEA Papers and Proceedings*, May 2020, 110, 215–219.
- , —, and —, “Salary History and Employer Demand: Evidence from a Two-Sided Audit,” *American Economic Journal: Applied Economics*, 2023.
- Amanatullah, Emily T. and Catherine H. Tinsley**, “Punishing female negotiators for asserting too much...or not enough: Exploring why advocacy moderates backlash against assertive female negotiators,” *Organizational Behavior and Human Decision Processes*, January 2013, 120 (1), 110–122.
- Babcock, Linda, Maria P. Recalde, Lise Vesterlund, and Laurie Weingart**, “Gender Differences in Accepting and Receiving Requests for Tasks with Low Promotability,” *American Economic Review*, March 2017, 107 (3), 714–747.
- , **Sara Lschever, Deborah Small, and Michelle Gelfand**, “Nice Girls Don’t Ask,” 2003, 81 (Harvard Business Review), 14–15.
- Baker, Michael, Yosh Halberstam, Kory Kroft, Alexandre Mas, and Derek Messacar**, “Pay Transparency and the Gender Gap,” *American Economic Journal: Applied Economics*, April 2023, 15 (2), 157–183.
- Barbanchon, Thomas Le, Roland Rathelot, and Alexandra Roulet**, “Gender Differences in Job Search: Trading off Commute Against Wage,” *The Quarterly Journal of Economics*, December 2020, 136 (1), 381–426.
- Becker, Gary S.**, *The Economics of Discrimination* Economic Research Studies, Chicago, IL: University of Chicago Press, 1957.
- Bertrand, Marianne**, “New Perspectives on Gender,” in “Handbook of Labor Economics,” Vol. 4, Elsevier, 2011, pp. 1543–1590.
- , **Claudia Goldin, and Lawrence F Katz**, “Dynamics of the Gender Gap for Young Professionals in the Financial and Corporate Sectors,” *American Economic Journal: Applied Economics*, July 2010, 2 (3), 228–255.
- Biasi, Barbara and Heather Sarsons**, “Flexible Wages, Bargaining, and the Gender Gap,” *The Quarterly Journal of Economics*, December 2021, 137 (1), 215–266.
- and —, “Information, Confidence, and the Gender Gap in Bargaining,” *AEA Papers and Proceedings*, May 2021, 111, 174–178.

- Blau, Francine D. and Lawrence M. Kahn**, “The Gender Wage Gap: Extent, Trends, and Explanations,” *Journal of Economic Literature*, September 2017, 55 (3), 789–865.
- Blundell, Jack, Emma Duchini, Stefania Simion, and Arthur Turrell**, “Pay Transparency and Gender Equality,” *American Economic Journal: Economic Policy*, 2025.
- Bowles, Hannah Riley, Linda Babcock, and Kathleen L. McGinn**, “Constraints and triggers: Situational mechanics of gender in negotiation.,” *Journal of Personality and Social Psychology*, 2005, 89 (6), 951–965.
- , —, and **Lei Lai**, “Social incentives for gender differences in the propensity to initiate negotiations: Sometimes it does hurt to ask,” *Organizational Behavior and Human Decision Processes*, May 2007, 103 (1), 84–103.
- Buser, Thomas, Muriel Niederle, and Hessel Oosterbeek**, “Gender, Competitiveness, and Career Choices \*,” *The Quarterly Journal of Economics*, August 2014, 129 (3), 1409–1447.
- Cahuc, Pierre, Fabien Postel-Vinay, and Jean-Marc Robin**, “Wage Bargaining with On-the-Job Search: Theory and Evidence,” *Econometrica*, March 2006, 74 (2), 323–364.
- Caldwell, Sydnee and Nikolaj Harmon**, “Evidence from Coworker Networks,” 2019, p. 105.
- Card, David, Ana Rute Cardoso, and Patrick Kline**, “Bargaining, Sorting, and the Gender Wage Gap: Quantifying the Impact of Firms on the Relative Pay of Women,” *The Quarterly Journal of Economics*, May 2016, 131 (2), 633–686.
- Chen, Jiafeng and Jonathan Roth**, “Logs with Zeros? Some Problems and Solutions,” *The Quarterly Journal of Economics*, March 2024, 139 (2), 891–936.
- Cortés, Patricia, Jacob French, Jessica Pan, and Basit Zafar**, “Gender Differences in Negotiations and Labor Market Outcomes: Evidence from an Information Intervention with College Students,” *NBER Working Paper 32154*, February 2024, p. w32154.
- , **Jessica Pan, Laura Pilossoph, Ernesto Reuben, and Basit Zafar**, “Gender Differences in Job Search and the Earnings Gap: Evidence from the Field and Lab,” *The Quarterly Journal of Economics*, November 2023, 138 (4), 2069–2126.
- Cullen, Zoe, Shengwu Li, and Ricardo Perez-Truglia**, “What’s My Employee Worth? The Effects of Salary Benchmarking,” *NBER Working Paper 30570*, October 2022, p. w30570.
- Cullen, Zoë**, “Is Pay Transparency Good?,” *Journal of Economic Perspectives*, February 2024, 38 (1), 153–180.

- **and Ricardo Perez-Truglia**, “The salary taboo privacy norms and the diffusion of information,” *Journal of Public Economics*, June 2023, *222*, 104890.
- Exley, Christine L. and Kirby Nielsen**, “The Gender Gap in Confidence: Expected but Not Accounted For,” *American Economic Review*, March 2024, *114* (3), 851–885.
- Exley, Christine L, Muriel Niederle, and Lise Vesterlund**, “Knowing When to Ask: The Cost of Leaning In,” *journal of political economy*, January 2020, *128* (3), 39.
- Jäger, Simon, Christopher Roth, Nina Roussille, and Benjamin Schoefer**, “Worker Beliefs About Outside Options\*,” *The Quarterly Journal of Economics*, January 2024, p. qjae001.
- Kessler, Judd B., Corinne Low, and Colin D. Sullivan**, “Incentivized Resume Rating: Eliciting Employer Preferences without Deception,” *American Economic Review*, November 2019, *109* (11), 3713–3744.
- Kleven, Henrik, Camille Landais, Johanna Posch, Andreas Steinhauer, and Josef Zweimüller**, “Child Penalties across Countries: Evidence and Explanations,” *AEA Papers and Proceedings*, May 2019, *109*, 122–126.
- Kugler, Adriana D., Catherine H. Tinsley, and Olga Ukhaneva**, “Choice of majors: are women really different from men?,” *Economics of Education Review*, April 2021, *81*, 102079.
- Leibbrandt, Andreas and John A. List**, “Do Women Avoid Salary Negotiations? Evidence from a Large-Scale Natural Field Experiment,” *Management Science*, September 2015, *61* (9), 2016–2024.
- Mas, Alexandre and Amanda Pallais**, “Valuing Alternative Work Arrangements,” *American Economic Review*, December 2017, *107* (12), 3722–3759.
- Niederle, Muriel and Lise Vesterlund**, “Do Women Shy Away from Competition? Do Men Compete Too Much?,” *The Quarterly Journal of Economics*, August 2007, *122* (3), 1067–1101.
- Robinson, Joan**, *The Economics of Imperfect Competition*, London: Palgrave Macmillan UK, 1969.
- Rosenman, Evan T. R., Santiago Olivella, and Kosuke Imai**, “Race and ethnicity data for first, middle, and surnames,” *Scientific Data*, May 2023, *10* (1), 299. Publisher: Nature Publishing Group.
- Roussille, Nina**, “The Role of the Ask Gap in Gender Pay Inequality,” *The Quarterly Journal of Economics*, February 2024, p. qjae004.
- Wiswall, Matthew and Basit Zafar**, “Human Capital Investments and Expectations about Career and Family,” *Journal of Political Economy*, 2021.