THE CENTRAL ROLE OF THE ASK GAP IN GENDER PAY INEQUALITY

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Abstract

The gender *ask gap* measures the extent to which women ask for lower salaries than comparable men. This paper studies the role of the ask gap in generating wage inequality, using novel data from Hired.com, an online recruitment platform for full-time engineering jobs in the United States. To use the platform, job candidates must post an *ask salary*, stating how much they want to make in their next job. Firms then apply to candidates by offering them a *bid salary*, solely based on the candidate's resume and ask salary. If the candidate is hired, a *final* salary is recorded. After adjusting for resume characteristics, the ask gap is 2.9%, the gap in bid salaries is 2.2%, and the gap in final offers is 1.4%. Remarkably, further controlling for the ask salary explains the entirety of the residual gender gaps in bid and final salaries. To estimate the market-level effects of an increase in women's ask salaries, I exploit an unanticipated change in how candidates were prompted to provide their ask. For some candidates in mid-2018, the answer box used to solicit the ask salary was changed from an empty field to an entry pre-filled with the median bid salary for similar candidates. Using an interrupted time series design, I find that this change drove the ask gap, the bid and the final offer gap to zero. In addition, women did not receive fewer bids or final offers than men did due to the change, suggesting they faced little penalty for demanding wages comparable to men.

JEL codes: J31; J16; J49

Keywords: Gender wage gap, gender ask gap, job search, online recruitment

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"We cannot change what we are not aware of, and once we are aware, we cannot help but change."

— Sheryl Sandberg *Lean In: Women, Work, and the Will to Lead*

1 Introduction

Over the past several decades, the raw gender pay gap in the U.S. has declined significantly, falling from about 40% in the 1960s to 20% today. While the raw gap has narrowed, the residual pay gap - the portion of the pay gap that cannot be accounted for by gender differences in measured qualifications - has stagnated at around 10% for the past 30 years (Blau and Kahn (2017)). In parallel, there is mounting evidence that women still have lower salary expectations than comparable men, especially at the top of the income distribution (Reuben, Wiswall, and Zafar (2017), Bergerhoff et al. (2019)). Taken together, these facts raise concerns that women's lower salary expectations contribute to the persistence of the residual pay gap (Babcock et al. (2003), Leibbrandt and List (2015), and Biasi and Sarsons (2020)).

This paper investigates how gender differences in salary demands influence the wage gap in a high-skilled online labor market. Recent survey evidence indicates that the majority of high-wage workers in the U.S. are asked to state their desired salary during the recruitment process (Agan, Cowgill, and L. K. Gee (2020)). Yet, quantifying the role of the candidates' desired salary in the determination of salary offers in traditional labor markets has proven challenging. Data on workers' salary demands is typically collected via surveys or laboratory experiments that may not capture the salary negotiations that actually arise in high stakes recruitments. In addition, available wage data usually provides information on only one side of the market: either the candidate's side (e.g., survey evidence on salary expectations) or the firm's side (e.g., administrative data on firm salary offers). No dataset simultaneously combines information on candidate salary demands and on how these demands influence their salary offers from firms.

To fill this gap, I analyze data from Hired.com, a leading online recruitment platform for full-time, high-wage engineering jobs. The key novelty of this platform is that it records previously unexplored components of the salary negotiation process. First, every candidate has to provide the salary they are looking for in their next job. This *ask salary* is visible to firms recruiting on the platform, along with the candidate's resume information. Second, companies signal their interest to candidates with a *bid salary*, indicating how much they would be willing to pay the candidate before interviewing them. Last, the platform records a *final salary* if the candidate is hired. Given that the average annual salary on the platform is \$120,000, the candidates on Hired.com are a highly relevant population for studying high-stakes wage bargaining.

Using data on more than 110,000 candidates over several years, I first document a 6.8% raw ask gap on the platform. After controlling for all the candidates' resume characteristics, the ask gap is 2.9%. In other words, women with resumes comparable to those of men ask for 2.9% less. This gap is both statistically significant and economically meaningful: it represents \$3,493 every year, on average. I also find significant heterogeneity in the ask gap. Using the Sorted Partial Effects method of Chernozhukov, Fernàndez, and Luo (2018), I find ask gaps ranging from 8.5% to -2.1%, with the largest gap arising among candidates who are not currently employed, have more experience, and fewer credentials.

Second, I measure the impact of the ask salary on firms' bid and final offer gaps. Using data on more than 460,000 bids, I find a raw bid gap on the platform of 3.7%. Adjusting for candidates' resume characteristics but excluding their ask salary leaves a 2.2% residual bid gap. When candidates' ask salaries are included as a control, this residual bid gap disappears. In other words, while resume characteristics can only reduce the bid gap by 40%, gender differences in ask salaries can essentially explain 100% of the bid gap. Similarly, for a given job, resume characteristics account for 3 percentage points of the 4.9% unadjusted bid gap, while further controlling for the ask salary brings the bid gap to zero. Remarkably, a linear model conditioning solely on candidates' resume characteristics explains 81% of the variation in bid salaries, while adding the ask salary to the controls raises the R^2 to 0.95, leaving little room for omitted variable bias. For the sub-sample of 7,582 hired candidates, gender differences in ask salaries explain nearly all of the gap in final offers. In particular, while conditioning on resume characteristics only narrows the final offer gap to 1.4%, adding the ask salary to the controls reduces the final offer gap to -0.9% and further controlling for firm fixed effects brings it to zero.

I find no evidence of discrimination against women at the extensive margin. In fact, conditional on their resume characteristics, women get slightly more bids than men and, conditional on interviewing, women are just as likely as men to get a final offer.

To estimate the market-level effects of an increase in women's ask salaries, I study an unanticipated feature change that affected a subset of candidates on the platform and induced women to ask for more. In mid-2018, Hired.com abruptly changed the way that some candidates were prompted to provide their ask salary. From the first year of the data to mid-2018, candidates stated their ask salary by filling out an empty text box. Starting in mid-2018, the answer box for

San Francisco software engineers was pre-filled with the median bid salary over the past 12 months for the candidate's combination of desired location, job title, and experience. In effect, this change gave candidates information on the typical offers received by similar candidates on the platform and provided them with an anchor to benchmark their own ask salary. Using an interrupted time series design, I show that the new framing of the ask salary elicitation eliminated the ask gap and rendered the bid gap insignificant. These results are driven by women asking for higher salaries after the reform. Further, I find no discernable impact on the number of bids that women received or the likelihood that they receive a final offer, suggesting that women had effectively been leaving money on the table.

This paper contributes to several lines of research. First, it integrates the ask gap into the prominent literature on gender wage gaps. The most common concept measured in this literature is the gender gap in realized wages (Blau and Kahn (2017), Olivetti and Petrongolo (2016)), but a more recent strand of the literature has investigated gender gaps in salary expectations (Reuben, Wiswall, and Zafar (2017), Bergerhoff et al. (2019)). Compared to expectations measures, the ask salary plays a direct role in the salary negotiation, as it is one of the few signals voluntarily transmitted to employers. Relative to survey measures, the Hired data have several strengths: large sample size, no missing values due to non-response, and real labor market relevance. Finally, the recruitment process on the platform allows for the direct measurement of the impact of candidates' ask gap on the firms' offer gap, while most studies only observe either the candidate or the firm side of the market. Some exceptions can be found in the literature on reservation wages (e.g. Le Barbanchon, Rathelot, and Roulet (2021)), but in contrast with the ask salary, reservation wages are not observable to firms.

Second, my research relates to the literature on gender differences in negotiation, especially at the top of the income distribution (Bertrand (2017), Goldin (2014), and Garbinti, Goupille-Lebret, and Piketty (2018)). Most of the evidence in this literature comes from laboratory experiments (Babcock et al. (2003), Bowles, Babcock, and McGinn (2005), Small et al. (2007)) or surveys (Babcock and Laschever (2006)). These papers establish that, in the lab or in self-reported survey data, women have lower salary expectations, negotiate less and receive lower salary offers. I contribute to this literature first by providing evidence that women indeed ask for significantly less in high stakes environments and second by providing direct evidence that this gap is consequential for resulting salary offers.

Third, this paper speaks to a large empirical literature that explores gender discrimination in the hiring process using observational evidence (Kuhn and Shen (2013), Kuhn, Shen, and Zhang (2019)) or experiments (Goldin and Rouse (2000), Neumark (2004), Neumark (2018), and Rich (2014)). The main focus in this literature has been to estimate how the probability of being hired (or interviewed) differs across similar men and women when they apply for the same job. I take the reverse approach, exploring the propensity of companies to apply to comparable candidates. In the Hired.com setting, I find no evidence of discrimination against women at the extensive margin: women in fact get slightly more interview requests than men and, conditional on interviewing, women are just as likely as men to get a final offer.

Finally, my research contributes to a strand of literature in behavioral labor economics that examines the role of information in the job search process and salary decisions. Recent papers (Bennedsen et al. (2019), Baker et al. (2019), Cullen and Pakzad-Hurson (2020) and Cortés et al. (2021)) illustrate how accurate information and pay transparency can affect the gender wage gap in different settings. For instance, Baker et al. (2019) examined the impact of public sector salary disclosure laws on university faculty salaries in Canada. They found robust evidence that the laws reduced the gender pay gap between men and women by approximately 30 percent, primarily through more rapid wage growth for women. Rigdon (2012) shows that, in a "Demand-Ultimatum" game where participants have to share $20, women initially request less than men but when they are informed about the amounts demanded by other participants, they start requesting the same as men. Similarly, the change in the ask salary elicitation I exploit shows candidates the median bid salary on the platform for a comparable profile. I find that this change eliminates the ask and the bid gap, without affecting the relative number of bids received by women or their relative chances of getting a job offer.[1] In contrast, recent lab-based evidence finds that nudging women to "lean in" can result in worse outcomes for them (Exley, Niederle, and Vesterlund (2020)). Better understanding the contexts and conditions under which asking for higher pay benefits, rather than harms, women is an important avenue for future research.

The remainder of this paper proceeds as follows. Section 2 provides details on the empirical setting. Section 3 presents more information on the data. Section 4 describes the empirical strategy to estimate the ask gap and documents its existence and magnitude. Section 5 provides evidence on the impact of the ask gap on the bid gap and final salary gap. Section 6 presents evidence

[1] This result adds to the broader evidence that seemingly light-touch interventions can have significant impacts on gender differences in labor search. For instance, Gee (2019) showed, in a field experiment, that seeing the number of applicants for a job posting on LinkedIn increased the likelihood that a person would finish an application by 3.5%. The effect was larger for women, therefore reducing the initial gender application gap.

that women are not discriminated against at the extensive margin. Section 7 details the reform on elicitation of candidates' salaries and reports estimates of the effects of the reform. Section 8 concludes.

2 Institutional setting

2.1 Market description

Several previous papers have studied online labor markets, such as Amazon MTurk, to explore channels of the gender pay gap (Litman et al. (2020); Gomez-Herrera and Mueller-Langer (2019)). These markets allow researchers to run experiments and to precisely record the impacts of experimentally assigned treatments on outcomes (hours worked, salary etc). However most of these markets offer task-based, remote, and low-wage jobs, and so even experimental evidence on bargaining on those platforms may not reflect bargaining behaviors in more traditional labor markets. Hired.com mostly features full-time, high-wage engineering jobs based in the U.S. In fact, 96.9% of the candidates on the platform state that they are looking for a full-time job with an annual salary, and most of those candidates are highly educated: 81.6% of them have at least a bachelor's degree and 41.4% have at least a master's degree. Accordingly, the average salary offered by firms on the platform is high ($119,548). In short, Hired.com should be thought of as a job board for well-qualified candidates, with a focus on the tech industry.

The candidates and jobs on Hired.com are comparable to those listed on other recruitment platforms for similar careers.[2] For instance, the most common profile on Hired.com is a software engineer in San Francisco. As of April 2020, Glassdoor's average salary for this profile was $119,488 and Paysa's was $132,000[3]. Hired's salary for such profiles is $129,783, which is in the bracket between Glassdoor's (lower bound) and Paysa's (upper bound) salaries. The Hired.com sample also features profiles with different levels of seniority. For instance, among SF software engineers, 6% have 0-2 years of experience in software engineering, 21% have 2-4 years of experience, 23% have 4-6 years of experience, 35% have 6-10 years of experience, 9% have 10-15 years of experience, and 6% have more than 15 years of experience. This distribution is similar to the one found on Payscale

[2] Relative to job candidates nationwide, candidates on Hired are more likely to work in tech (61.7% of the candidates are software engineers) and to live in the Bay Area (31.6% of them do). The platform therefore has a clear focus on the tech industry compared to job boards such as Glassdoor.

[3] Paysa is a personalized career service offering salary compensation and job matching for corporate employees. It is a useful reference for comparing employee salaries in the tech industry.

for this combination of job and location.[4] Additionally, the 6,532 firms in the Hired sample are also representative of the digital economy ecosystem: they are a mix of early stage firms, more mature start-ups (e.g Front, Agolia), and larger, more established firms (e.g. Zillow, Toyota). Finally, the gender ratio on Hired.com (20.8% female) is similar to the general population of computer science and engineering graduates.[5] This gender imbalance in a high-wage sector makes the tech industry a particularly interesting sector in which to study the gender pay gap for top earners. In fact, this paper is not the first to use engineering as a flagship for documenting gender differences in negotiation. Sheryl Sandberg, the Chief Operating Officer of Facebook, leveraged her experience in this industry to urge women to "lean in" and start negotiating more, in her 2013 book *Lean In: Women, Work, and the Will to Lead*.[6]

The tech sector has played a central role in fostering national economic growth and competitiveness in the past decade (Barefoot et al. (2018)). Kerr and Robert-Nicoud (2020) summarized tech clusters' large contribution to innovation as follows: between 2015 and 2018, San Francisco, while representing only 2.5% of the U.S. population, accounted for 48.1% of venture capital investment, 18.4% of granted patents, and 11.7% of highly-educated workers in top 10 R&D industries. Since this sector represents a large and growing share of high-wage workers, it is important to understand the dynamics of this particular labor market. Yet, while the gig economy has been studied for low-wage workers (see Cook et al. (2018), Caldwell and Oehlsen (2018) and Abraham et al. (2018)), there is less evidence on high-wage workers in this sector.[7]

2.2 Recruitment process

The hiring process on Hired.com differs from a traditional job board in two main ways. First, on a traditional job board, firms post a job description (that may contain a posted wage) and then candidates apply to each posted job separately. Afterwards, the company interviews a selection of applicants and decides whether and who to hire.[8] In contrast, on Hired.com, companies apply to candidates based on their profiles on the platform, then candidates decide whether or not to interview with the company based on the job description and bid salary they receive. Second, in

[4] Payscale's page for SF software engineer profiles

[5] Chamberlain and Jayaraman (2017) showed that among science and engineering graduates, only 26% are female, and a disproportionate number of these female graduates end up working in fields other than computer science.

[6] This book found a large audience: it was on the *New York Times* best-seller list for more than a year and has sold 4.2 million copies worldwide. Evidently it struck a chord for many women, in the tech industry and beyond.

[7] A few recent exceptions are Murciano-Goroff (2018) Boudreau and Kaushik (2020) and Abraham and Stein (2020).

[8] A "target salary" can potentially be backed out by observing what jobs candidates select into (Marinescu and Skandalis (2019)), but the ask salaries are not directly observable.

a wage posting context, candidates' demands do not directly influence firms' posted wages. In contrast, on Hired.com firms make salary offers only after observing the candidates' resumes and asks.

Formally, the recruitment process can be divided into the following three sequential steps, also described in Figure I:

Supply side: Candidates create a profile that contains standardized resume entries (education, past experience, etc.) and, crucially, the salary that the candidate would prefer to make. We denote this the *ask salary*. Figure B.1 is a screenshot of a typical candidate's profile, and Table C.1 further provides an exhaustive listing of profile fields. In short, every profile includes the current and desired location(s) of the candidate, their desired job title (software engineering, web design, product management, etc.), their experience (in years) in this job, their top skills (mostly coding languages such as R or Python), their education (degree and institution), their work history (i.e., firms they worked at), their contract preferences (remote or on-site, contract or full-time, and visa requirements), as well as their search status, which describes whether the candidate is ready to interview and actively searching or simply exploring new opportunities. Importantly, the ask salary is prominently featured on all profiles since it is a required field.

Demand side: Firms get access to candidate profiles that match standard requirements for the job they want to fill (i.e., job title, experience, and location). To apply for an interview with a candidate, the company sends them a message - the *interview request*- that typically contains a basic description of the job as well as, crucially, the salary at which they would be willing to hire the candidate. We will denote this the *bid salary*. Figure B.2 is a screenshot of a typical message sent to a candidate by a company. The bid salary is prominently featured in the subject line of the message and is required to be able to send the message. The equity field also exists but is optional.

Demand meets supply: Hired.com records whether the candidate accepts or rejects the interview request. While interviews are conducted outside of the platform, Hired.com gathers information on whether the company makes a final offer of employment to the candidate and at what salary. We refer to this as the *final salary*. It is important to note that the bid salary is non-binding, so the final salary can differ from the bid. Finally, we observe whether the candidate accepts the final salary offer, in which case the candidate is hired.

2.3 Relevance of the recruitment process to other wage bargaining settings

While the ability to record granular steps of the negotiation process is unique, some of these steps are common to a large share of interviews, especially for high-wage candidates. For instance, using a 2019 survey of 504 Americans in the labor force, Agan, Cowgill, and L. K. Gee (2020) found that 55% of workers making above $68,000 a year were asked for their desired salary during the recruitment process (compared to 42% of the full sample). Therefore, Hired.com makes explicit what effectively occurs during the majority of high-wage interviews: candidates are asked to disclose their desired salary. There is also evidence that, in a non-trivial share of wage negotiations, candidates are asked for their desired salary before the company makes them an offer. For instance, in a Google survey of approximately 400 subjects, Barach and Horton (2021) found that, among candidates who negotiated their wages, 39.2% proposed a wage before the firm did. It is therefore not uncommon for the candidate to state their ask first, although, in more traditional settings it might occur later in the recruitment process (e.g. after, rather than before, the interview). One key advantage of the Hired.com setting is that, by observing both the bid and the final salary, I can explore how the initial ask relates to the bid and how subsequent negotiations during and after the interview may influence the final offer.

3 Data

3.1 Sample size

Tables I and II reports the sample sizes for the main units of observation on the candidate and company side respectively . The final dataset has 113,777 unique candidate profiles, 39,839 jobs, and 6,532 firms. Each job is sent out on average to 11.6 candidates so that there are a total of 463,860 interview requests ($\approx$ 39,839 $\times$ 11.6) sent out by firms, resulting in 7,582 final offers. The data spans several recent years but, per the research contract signed with the company, the exact start and end dates of the period for which the data was made available cannot be disclosed, to preclude inference about market shares.

3.2 Gender

Gender is an optional field on the profile and only 50% of the candidates self-declared their gender. In order to obtain gender data for the other 50%, I use a standard prediction algorithm based on first names.[9] The prediction can take 5 values: "male", "mostly male", "ambiguous", "mostly female", and "female". When available, I used the self-declared gender of the candidate; otherwise I impute gender using the algorithm, assigning a gender only to candidates for whom the algorithm predicted "male" or "female". Reassuringly, for the sub-sample that self-declared their gender (i.e. 50% of the full sample), I verified that the algorithm guessed incorrectly only 0.6% of the time. Firms are informed of the gender of essentially all candidates since most profiles contain pictures and first names. Combining explicit declarations and imputation, I can classify 84.6% of the profiles. Women represent 20.8% of the classified sample, while men represent the remaining 80.2% .[10]

3.3 Candidate summary statistics

Table I provides information on the resume characteristics of the candidates. They have, on average, 11.3 years of experience, which corresponds to the industry average in this sector (see Visier and Insights (2017)). They are highly educated: 97.6% of the candidates have at least a bachelor's degree and 41.4% have at least a master's degree. Candidates also stand out by the quality of the education they received: 9.4% of the sample obtained one or more of their degrees from an IvyPlus institution.[11] Given that the platform targets engineers, it is not surprising to observe that 55.2% of the candidates have a degree in Computer science and that 61.7% of them are looking for software engineering positions. The platform's focus on the tech industry is also reflected in the location of its candidates: about a third of them are looking for a job in the Bay Area. Illustrating the fact that the digital economy relies not only on U.S. citizens but also on immigrants, 13.6% of the candidates are looking for firms that can sponsor a visa to work in the U.S. Finally, about 3 out of 4 candidates are looking for job-to-job transitions while the other 25% are not currently employed, with an average unemployment duration of eight months.

Male and female candidates differ in experience, occupation, and location. On average, women have 1.6 fewer years of experience than men in the sample. However, mirroring the overall U.S. population, the women appear to be more educated (45.2% of them have a master's vs 40.3% of the men). With respect to occupation, 66.6% of the men are looking for software engineering positions,

[9] The algorithm can be found at https://pypi.org/project/SexMachine/

[10] As discussed in Section 2.1, the over-representation of men in the dataset simply reflects the fact that the platform is focused on software engineering, a field well-known for its gender imbalance.

[11] As defined by Chetty et al. (2017), the IvyPlus institutions are the eight Ivy League institutions + U. Chicago, Stanford, MIT, and Duke. Additionally, I include the schools with the top five highest-ranked programs in engineering on the annual U.S. News college ranking: UC Berkeley, California Institute of Technology, Carnegie Mellon University, and Georgia Institute of Technology.

while only 43.2% of the women are. The other women are mainly looking for either a web design (16.6%) or a product management position (11.4%). Accordingly, the share of men with a computer science (CS) degree is higher (57.2% vs. 47.7%). Finally, women are more likely to be looking for a job in the Bay Area (37.5% vs 30.0%).

Candidates can also express preferences about the company size and industry of their ideal employer, as well as their preferred focus in their next job. Around 75% of candidates express at least one preference. Appendix Table C.8 presents gender differences in these preferences controlling for candidates' resume characteristics. The main take-away from this table is, that while men and women differ in their preferences in the expected direction (e.g. women are more likely than men to prefer firms that are socially conscious, more likely to seek a mentorship role and less likely to seek a leadership role), the differences are quite small in magnitude (e.g. 18.9% of men express a preference for leadership, that share is only 0.5 percentage points lower for women with the same resume characteristics).

3.4 Firm summary statistics

Table II provides information on firm characteristics such as revenue, age, size or industry, for the subsample of companies that list them on Hired.com. Around a quarter of companies are early stage firms that were founded within 4 years of the end of the sample period, report less than 1 million in revenue and almost half the firms enlist between 1 and 50 employees. Medium sized companies or matured start-ups with 51 to 500 make up around 40% of the sample and the remaining 11% consist of established companies with more than 500 workers. The overall distribution of revenue is strongly right skewed with a median of 15 million USD and a mean of 708.5 million USD. Consistent with candidates current and preferred location, the most common location among firms on the platform is the San Francisco Bay Area (42%), followed by New York (18%) and Los Angeles (8%). The three most frequent industries in which companies operate are Enterprise Software (15%) , Banking & Finance (10%), as well as Business Analytics (8%). Firms can also list benefits on their platform profile which they typically offer to their employees - the three most common being all related to health related insurances (health (83%), dental(81%) and vision (81%) insurance) followed by company supported pension plans (74%). The average number of listed benefits is 8.5 (and the median is 6).

3.5 Candidate / Firm interactions

For a given job, firms contact on average 11.6 candidates. One key feature is that, for the same job, there can be as many bid salaries as there are candidates contacted. In fact, only 2.4% of jobs offer the same bid salary to all candidates. In other words, in the vast majority of cases, firms offer the same job to multiple candidates at different bid salaries. The within-job variation in salaries is actually quite large: the average standard deviation of offers for a given job is $16,575. On the candidate side, the average number of interview requests, conditional on receiving at least one, is 4.5, and candidates agree to an interview about 62% of the time. There are some gender differences in this process. On average, a male candidate receives 9.5% more interview requests than a female candidate. However, as we will see in Section 6, once we control for the candidates' resume information, women are actually slightly more likely to get interview requests than men.

3.6 Job and candidate search

Once a candidate profile is reviewed and approved by Hired.com, it goes "live" on the platform, making it visible to firms. The default length of a spell on the platform is two weeks. Candidates can then request to remain visible for two to four additional weeks. 55% of the candidates are live for two weeks, 22% remain visible for four, and the remaining 23% are visible for six. In the sample, 84% of the candidates only had one spell on the platform, 11% went on two different spells on the platform, 3% had three spells on the platform, and the remaining 2% had more.

On the company side, a separate job identifier is created for each job that the company wants to fill. The company may be looking to hire several candidates for the same job. If we restrict the sample to jobs that find a match on the platform, 77.3% of them hire a single person and 14.3% hire two.

Only a subset of the jobs find a suitable candidate on the platform, and similarly only some of the candidates are hired on the platform. Firms that find a candidate for the job exert additional search efforts on the platform: on average, they send almost three times as many interview requests to candidates than the average (30.2 vs 11.6). In the same vein, candidates that do find a job received about 1.5 times as many interview requests as the average candidate (6.6 vs 4.5) and they are somewhat more likely to accept an interview request.

3.7 How do the ask and bid salaries relate to more traditional measures?

This paper measures two previously unobserved components of the salary negotiation: the ask salary and the bid salary. Therefore, it is important to understand what these concepts actually capture and how they relate to more traditional measures. In particular, how does the ask salary compare to a salary expectation or a reservation salary? In addition, given that the bid salary is non-binding, how does it relate to final offers?

I label as the ask salary the answer that candidates give to the question: "what base salary are you looking for in your next role?". Candidates record this ask knowing that it will be visible to hiring firms on the platform. The closest previously measured concept is salary expectations, i.e., how much people expect to make in their next job (e.g., Reuben, Wiswall, and Zafar (2017)). The key conceptual difference with the ask salary is that salary expectations measured in survey data are not observable by firms. This difference has important implications as the ask salary is part of the salary negotiation process while salary expectations are measured outside of a recruitment context. Given the strategic game at play in salary negotiation, candidates may reveal an ask that is different from their "true" salary expectations in order to maximize their salary outcome.

Candidates can adopt different strategies for the choice of the ask salary. For instance, some candidates may choose to record their reservation salary, the lowest salary at which they would accept a job offer. Others may provide an estimation of their market value. Finally, some could put the highest salary at which they believe they can be hired. These possible interpretations are, to some extent, testable since they give rise to different responses to the bids received. If the ask salary is interpreted as a reservation wage, then we should observe that very few candidates accept interviews with firms that make bids below their ask. Conversely, if the ask is less binding, we should see some candidates interviewing with firms that bid below their ask. We test these predictions in Figure II, plotting the probability of acceptance of an interview request against the ratio of the bid to ask salary.

The first striking fact is that, even when a bid is below the ask (that is $\frac{bid}{ask} < 1$ on the x-axis), candidates still accept the interview request on average 49% of the time. Therefore, the ask salary isn't strictly speaking a reservation salary, although it should be noted that Krueger and Mueller (2016), who directly elicited reservation wages, still found that 44% of final salary offers below the person's reservation wage were accepted. One could object that, since bids are not binding, candidates are accepting bids below their asks in the hope of negotiating higher final salaries.

However, 26% of the accepted final offers are below the candidate's ask. The second important fact is that candidates do seem to react to higher bids: the probability of acceptance is an increasing function of $\frac{bid}{ask}$, especially in the neighborhood of $\frac{bid}{ask} = 1$. Interestingly, there is no detectable difference between men and women in their acceptance behavior.

The distribution of $\frac{bid}{ask}$ illustrates the fact that companies rely heavily on the candidates' ask to make their bids: 77.3% of the offers are made exactly at the ask salary, while 7.5% are made above and 15.2% are made below. On average, bids are \$2,116 below the asks.

When declining an interview request, candidates provide a reason for their decision, and 58% of them do so. The candidates can choose from justifications such as "company culture," "company size," and "insufficient compensation." The latter is the justification I label as "bid too low." Figure B.3 relates the share of candidates listing "bid too low" as the reason for turning down the interview request to $\frac{bid}{ask}$. As expected, candidates are much more likely to list "bid too low" as a reason for their decision when $\frac{bid}{ask} < 1$. In particular, while this reason is virtually never brought up when the ask is equal to or above the bid, it explains more than 31% of the rejections when the bid is less than 0.8 times the ask, and it is still mentioned in 12.5% of the justifications when the bid is between 0.8 and 1 times the ask.[12]

The bid salary is what firms declare they are willing to pay the candidate solely based on their profile, before any interaction with them. The final salary is offered to a candidate at the hiring stage. Given that companies are by no means contractually bound by their bids, final salaries may differ from bids. Figure III shows that the relationship between the two is linear, except at the very top, and the slope is close to one. Additionally, 36% of all final offers are identical to the bid and 78% of all final offers are within \$10,000 of the bid.

4 Documenting the gender ask gap

In this section, I document the existence of a 2.9% gender ask gap, which is both highly statistically significant (1% level) and economically meaningful: it represents \$3,493 in annual salary, on average.

[12] A survey of more than 3,600 candidates on the platform for the Hired Brand Health report confirmed that compensation plays a central role in their job decisions. Indeed, 53% of candidates report that compensation is the most important thing they look for in a company, followed by company culture (42%).

4.1 Graphical evidence

Figure IV plots kernel density estimates of the distributions of male and female ask and bid salaries. There are two striking patterns in these graphs. The first is that men's and women's distributions have a similar shape, except that the females' distributions are shifted to the left and the male's second peak, at 120K, has more mass than the women's. On average, women ask for \$6,826 less than men (\$115,116 vs \$121,942)[13] and receive bids that are \$5,430 lower than men (\$115,290 vs. \$120,720). However, at this stage, the ask and bid gaps could merely reflect differences in resume characteristics such as job title or experience. The second, more interesting, fact is that the ask and bid salary distributions are quite close. This is the first piece of evidence in a pattern I will document throughout the paper: firms closely follow individuals' asks.

4.2 The gender ask gap: Methodology

Following the previous literature, we define the raw gender ask gap as the coefficient β_0 in the regression:

$$Log(Ask_i) = \alpha + \beta_0 Female_i + \gamma_t + \epsilon_i \tag{1}$$

where Ask_i is the ask salary of candidate i, $Female_i$ is a dummy equal to one if the candidate is female, γ_t is the Month $\times$ Year fixed effect, and ϵ_i is the error term. When collapsing the data to the candidate level, I select the first listed ask of each candidate.[14]

The adjusted gender ask gap is given by the coefficient β_0 in the regression:

$$Log(Ask_i) = \alpha + \beta_0 Female_i + \beta_1 X_i + \gamma_t + \epsilon_i \tag{2}$$

where the controls X_i are the candidates' resume characteristics, as described in detail in Appendix Table C.1. These controls include the variables we typically find in the gender pay gap literature using CPS or PSID data (e.g., education level and job title category), as well as more granular resume characteristics capturing, for instance, education quality and work history. These controls can be classified in three groups. First, there are categorical variables from the required candidate profile entries that we can use unaltered in the regression. Second, there are controls that need some processing: for example, education is indicated on profiles with all degrees and institutions.

[13] The average asks are weighted by the number of offers received; the unweighted ask gap is larger, at \$8,853.

[14] The results are qualitatively the same if we opt for the last ask salary (Appendix Table C.3) or if we treat each spell of the candidate as a different observation.

This information is processed into new variables that reflect the level (highest degree achieved) and quality of education (dummy for whether the candidate graduated from an IvyPlus school). Third, some controls were extrapolated either from the candidates' profiles or their meta information. For instance, I control for whether the candidate is currently employed, which is computed from the candidate's employment history. I also control for the number of past spells on the platform to capture potential learning effects. In short, these resume controls are:

- Raw required candidate profile entries:
  - desired job (e.g., software engineering, design, data analytics).
  - experience in this job (0-2 years, 2-4 years, ..., 15+ years).
  - listed skills (mostly these are coding skills such as HTML, Java, C, Python, etc.) and preferences over firm characteristics.
  - current and desired location(s).
  - contract preferences (remote or on-site, contract or full-time, and visa requirements).
  - search status (e.g. actively looking for a new job or just browsing).
  - number of people managed in current job (0, 1-5, 6-10, 11-20, 20+).
- Required candidate profile entries that I processed into new variables:
  - Education controls: I transformed the required education fields on the profile (institution, degree, and year of graduation) into 4 variables: Education level (High school, Associate's, Bachelor's, Master's, MBA, and PhD), a Computer Science (CS) degree dummy, a IvyPlus dummy, the average global ranking as reported on Webometrics of all schools the candidate attended, and also use the year of graduation in its raw form.
  - Work history controls: I transformed the list of firms the candidate worked at into a dummy for whether the candidate has ever worked for an "elite" tech company (Facebook, Amazon, Apple, Netflix, and Google).
- Controls that can be inferred from the candidate's profile, specifically:
  - Employed dummy for whether the candidate is currently employed.
  - Number of days since last job (equal to zero if currently employed).
  - Total experience in years (also squared).
  - The number of previous spells on the platform (to capture potential learning effects of using the platform).
  - Whether the candidate included a link to either a personal website or to the candidate's

LinkedIn profile.

In the regression tables reported here, I reorganize these controls in meaningful groups (for instance, putting together all controls that relate to the candidate's employment history).

An alternative perspective on the ask gap is to consider each interview request a candidate receives as a separate observation. Column (7) of Table III therefore implements the following strategy:

$$Log(Ask_{ib}) = \alpha + \beta_0 Female_i + \beta_1 X_{ib} + \gamma_t + \epsilon_{ib} \tag{3}$$

where Ask_{ib} is the ask salary of candidate i when he or she receives his or her b'th bid, $Female_i$ is a dummy equal to one if the candidate is female, γ_t is a Month × Year FE, ϵ_{ib} is an error term, and t is a function of i and b, $t(i, b)$, the time at which candidate i received bid b. In this specification, a candidate that never gets a bid will not appear, while a candidate who receives four bids will appear four times. For a given person, the ask salary we will use is the one that the company saw when making its bid at time t. Therefore, since a candidate can update his or her ask over the course of the spell or across spells, this candidate can appear with different asks in the regression at the candidate × interview request level. The advantage of this regression is that the units of analysis are the same as those in Table V, which investigates the effect of the ask gap on the bid gap.

4.3 Main results

Estimates of β_0 in equation 1, reported in Table III Column (1), indicate that there is a 6.8% raw ask gap between men and women. Once we have linearly controlled for all the resume characteristics from the candidate's profile in Column (5), the adjusted ask gap from equation 2 is 2.9%. This gap is both statistically significant and economically meaningful: it represents $3,493 in annual salary, on average.[15] Columns (2) to (5) progressively add the resume characteristics detailed in Appendix Table C.1. This exercise identifies which resume controls reduce the gender ask gap, from a raw 6.8% to an adjusted 2.9%. Column (6) includes fixed effects on candidates' most recent company and the adjusted gender ask gap goes to 3.2%. Further, I implement a selection exercise on observed and unobserved variable following Altonji, Elder, and Taber (2005). I obtain $[-0.029; -0.013]$ as a bounding set for β[16] (see Appendix Table C.4). Since 0 does not belong to this set, I can reject the null of a zero of the gender ask gap.

[15] See Appendix Table C.6, which runs the ask salary in dollars instead of the log on the same controls.

[16] I use the standard assumption that δ and R_{max} are 1

Adding controls for experience, location, and job title first narrows the gap down to 4.4% (Column (2)). This is mostly due to women having on average less experience or opting for lower-paid occupations. If anything, adding education controls (Column (3)) increases the ask gap by 0.3%. This is in line with recent studies showing that women have surpassed men in educational outcomes. The effect of the choice of major is likely already captured by the job title variable added in Column (2), so adding the education control mostly captures the level and quality of education. Men and women have similar work preferences, so adding these controls in Column (4) does not affect the ask gap. Adding employment history in Column (5) takes the gender gap further down to 2.9%. This is mostly driven by the coding skills listed on candidates' profiles, not by differences in exposure to an "elite" tech company in the past. In particular, women are less likely than men to list high-demand coding skills such as JavaScript (34.1% of women list it, compared to 41.8% of men) or Python (24.2% of women list it, compared to 29.9% of men). This gap in listed skills persists, even after controlling for occupation.[17]

Table C.5 provides information on the coefficients on variables aside from the female dummy. These coefficients affect the ask salary in the expected way: more experience and more education are associated with higher asks. For instance, keeping other variables constant, an individual with 2 to 4 years of experience in their current occupation tends to ask for 10.6% more than a candidate with 0 to 2 years of experience in that occupation. In a similar fashion, the coefficient on the employment dummy is positive and significant: all else equal, job-to-job switchers ask for 6.9% higher salaries than candidates that are not currently employed. Finally, more education also leads to higher ask salaries: all else constant, candidates whose highest degree is a PhD ask for 6.5% more than candidates whose highest degree is a master's.

4.4 Heterogeneity in the ask gap

To explore the degree of heterogeneity in the ask gap with respect to the underlying resume characteristics, I estimate a model that fully interacts the female dummy with the resume characteristics of the candidates. Following Chernozhukov, Fernàndez, and Luo (2018), I summarize these results using the sorted effect method for interactive linear models. This method reports the percentiles of the partial effects in addition to the average effect.

[17] Murciano-Goroff (2018) found that, on an online recruitment platform, female programmers with previous experience in a programming language were 9.10% less likely than their male counterparts to self-report knowledge of that programming language on their resume. Therefore, it could be that the listed skill gap between men and women on Hired.com reflects a gap in the propensity to list a programming language, rather than a gap in the actual experience in this language.

Figure V plots the estimates and 95% confidence sets of the population average partial effect (APE) and sorted partial effect (SPE) for the ask gap. The estimates range from 8.5% to -2.1%. In other words, there exists a subgroup of female candidates for whom the ask gap is close to 3 times as large as the APE, and there is a subgroup of women who actually ask for higher salaries than similar men. Table IV reports the results of the classification analysis, comparing the resume characteristics of people with the highest and lowest SPEs. In line with previous findings on the gender pay gap over the lifecycle (Goldin et al. (2017)), I find that the group with the largest ask gap (8.5%) is more experienced (13 years vs. 7 years of total experience). I also find that they are more likely to be unemployed, with longer unemployment spells, less likely to have a computer science or an IvyPlus degree, and less likely to list highly-demanded coding skills.

Given that experience is the resume characteristic that captures the greatest share of heterogeneity, I further explore its effect on the ask gap in Figure VIa, which plots the coefficient on the female dummy in Equation 2 estimated separately for different experience groups. The ask gap increases considerably with experience: it is actually insignificant for the 0-6 years of total experience group and is only 1-1.5% for the 6-8 years of experience group, but it jumps to about 4% for the 8-15 years of experience group. The largest gap, for candidates with more 15-20 years of experience, reaches 5.4%.[18] While it is beyond the scope of this paper to explain this gradient,[19] my analysis of the reform described in Section 7 demonstrates that a simple change in the way the website prompts candidates to provide their ask salary narrows the ask gap down to zero, even for candidates with more experience.

4.5 External validity

While there is no direct evidence on the ask gap in other datasets, the 6.8% raw ask gap I observe is comparable to the raw gender pay gap among computer engineers, who comprise much of the Hired sample. Specifically, the gender pay gap in computer engineering calculated using U.S. Census Bureau's 2016 American Community Survey is 8%.

Further, to benchmark the adjusted ask gap estimate of 2.9%, it is useful to analogize the ask salary to related concepts like survey expectations or reservation wages. The 2.9% estimated gap

[18] These figures illustrate how the ask gap increases with total number of years of experience, irrespective of the candidate's experience in his or her current occupation. We observe a similar gradient when exploring the experience of the candidate in his or her current occupation.

[19] As documented in Kleven, Landais, and Søgaard (2019) it could be that the increasing ask gap is reflective of the motherhood penalty. It could also be the case that, as women climb up the job ladder and negotiation becomes more central to the determination of wages, they are more likely to ask for less.

is on the lower end if I compare it to studies based on survey data. For instance, Krueger and Mueller (2016) found an 8.3% reservation wage gap in their survey of unemployed workers in New Jersey. However, recent papers using large administrative datasets have found similar estimates for closely related gender gaps. For instance, Le Barbanchon, Rathelot, and Roulet (2021) found a 3.6% residual gender reservation wage gap in France, using administrative data from unemployment insurance claimants. Fluchtmann et al. (2020), using data from Danish UI recipients, showed that after conditioning on a rich set of observables, women apply to jobs with a wage that is 1.9 percent lower than men. Both papers share with mine a large and reliable set of observations and controls. This likely explains why Le Barbanchon, Rathelot, and Roulet (2021) find an R^2 in their gender reservation wage gap regressions that is similar to the R^2 in my gender ask gap regressions (0.73 for them vs 0.71 in Column (5) of Table III). In comparison, most gender wage gap studies have R^2 in the range of 0.4-0.5 (for a review of R^2 in gender pay gap studies, see Table 10 in O'Neill and O'Neill (2006)).

5 The central role of the ask gap in gender pay inequality

Whether the 2.9% residual ask gap impacts the gender pay gap on the platform is an empirical question. Indeed, firms could value skill and experience regardless of what the candidates ask for and we would observe no gender differences in the bids sent by firms to candidates or in the final offers extended to hired candidates. In this section, I show that there is a 3.7% raw gender bid gap on the platform. Adjusting for candidates'resume characteristics but excluding their ask salary narrows this bid gap by 40%, leaving a 2.2% residual bid gap. When candidates' ask salaries are included as a control, this residual bid gap disappears.

5.1 The gender bid gap: Methodology

To empirically test the relationship between the bid gap and the candidates' resume characteristics and ask salary, I proceed in three steps. First, I estimate the raw gender bid gap. Then, I estimate how much of the bid gap can be explained with the candidates' resume characteristics. Finally, I estimate the effect of the ask salary on the bid gap, with and without the resume characteristics controls. Formally, these three models can be written as:

Model 1:

$$Log(Bid_{ib}) = \alpha + \beta_1 Female_i + \gamma_t + \epsilon_{ib} \tag{4}$$

Model 2:

$$Log(Bid_{ib}) = \alpha + \beta_1 Female_i + \beta_2 Equity_{ib} + \beta_3 X_{ib} + \gamma_t + \epsilon_{ib} \tag{5}$$

Model 3a:

$$Log(Bid_{ib}) = \alpha + \beta_1 Female_i + \beta_4 Log(Ask_{ib}) + \epsilon_{ib} \tag{6}$$

Model 3b:

$$Log(Bid_{ib}) = \alpha + \beta_1 Female_i + \beta_3 X_{ib} + \gamma_t + \beta_4 Log(Ask_{ib}) + \epsilon_{ib} \tag{7}$$

where $Log(Bid_{ib})$ is the b'th log bid salary received by candidate i. X_{ib} and $Log(Ask_{ib})$ are respectively candidate i's resume characteristics and log ask salary, when he or she receives his or her b'th log bid salary. X_{ib} contains the same controls as in Table III Column (5), and γ_t is a $Month \times Year$ FE, where $t = t(i, b)$, the time at which candidate i received bid b. All regressions also include a dummy equal to one if the interview requests included an equity offer.

5.2 The gender bid gap: Results

The raw gender bid gap, as estimated by β_1 in Equation 4 and reported in Table V Column (1), is 3.7% and significant at the 1% level. Controlling for the resume characteristics in Column (2) of the same table only takes the gender pay gap down by 40%, to 2.2%. In other words, differences in resume characteristics, such as experience or coding skills, can only account for about a two fifths of the gender bid gap on the platform. In contrast, controlling for the ask salary alone in Column (3) eliminates the gender bid gap: the coefficient on the female dummy even becomes positive, although very small (0.2%). This result persists when we add back all the candidate resume characteristics in Column (4): the coefficient on the female dummy remains very close to zero (-0.2%). Finally, we can test whether the effect of the ask salary on the bid salary differs by gender. To do so, Column (5) adds the interaction between the log ask salary and the female dummy. The point estimate of that interacted term is small and insignificant (0.2%), therefore failing to reject the null that men and women realize identical returns to asking for more.

Taken together, these results draw a clear picture: women ask for 2.9% less than men, and this ask gap can almost entirely explain the bid gap on the platform. Additionally, this result holds when we add an interaction between gender and the ask salary: men and women have the same salary returns from asking for more.

A fundamental challenge in the gender pay gap literature is that the residual gap may not only capture differences in salary between otherwise similar men and women, but also the fact that the econometrician is limited in his or her ability to control for the full information set available to firms. The recruitment process on Hired.com mitigates this concern because firms must formulate their initial bids to candidates before they are able to interact with those candidates. Therefore, the bid salary is solely based on candidates' resume characteristics and their ask salary and, as a result, having access to candidates' profiles is essentially equivalent to controlling for the firms' full information sets at the time they make their bids. The R^2 in Table V validate this overlap between Hired.com data and the firm's information sets: the linear model conditioning solely on candidates' resume characteristics explains 81% of the variation in bid salaries (Column (2)), while adding the ask salary to the controls raises the R^2 to 0.95 (Column (4)), leaving little room for omitted variable bias.

The very high coefficient on the log ask salary in Column (3) illustrates the central role of the ask salary in explaining the bid salary: when we only control for the ask, a 1% increase in the ask salary is, on average, associated with a 0.96% increase in the bid salary. When adding resume characteristics to the regression (column (4)), the coefficient on the log ask salary decreases in magnitude: part of the correlation between ask and bid salary is due, for instance, to the fact that individuals with more experience will ask for more and also have a higher market value. However, the coefficient remains remarkably high at 0.85. Taken at face value, this suggests that the elasticity of bid salary to a candidate's ask is 0.85. However, I do not find evidence that candidates can continuously increase their asks and expect to receive higher bids. In particular, the coefficient on the square of log ask is negative.

Figure VI shows that the bid gap varies by experience and illustrates how differences in the ask salary can account for this heterogeneity. Figure VIb plots the coefficient on the female dummy in equation 5 for different sub-groups of experience. The pattern in this figure mirrors Figure VIa: the bid gap follows the ask gap and increases with experience. However, when we add the ask salary as an explanatory variable in Figure VIc, the heterogeneity in experience disappears. Therefore, the difference in bid gap between more and less experienced women is entirely explained by differences in their asks.

5.3 External validity

The adjusted bid gap on the platform (2.2%) is smaller than the residual pay gap found in population surveys such as the PSID or the CPS. For instance, Blau and Kahn (2017) found a 8.4%

adjusted gap in the 2010 PSID. However, when focusing on similar populations (i.e., similar datasets with granular resume information and/or engineering majors), studies have found pay gaps closer to my estimate. For intance, Chamberlain, Zhao, and Stansell (2019) reported a 5.4% adjusted pay gap in the Information Technology industry on Glassdoor in 2019. Using administrative UI datasets with granular resume information, Fluchtmann et al. (2020) and Le Barbanchon, Rathelot, and Roulet (2021) respectively found a 1.9% residual wage gap in Denmark in 2015-2017 and a 3.7% residual wage gap in France between 2006 and 2012. This result further aligns with Goldin (2014), who postulated that among top earners, the wage gap is smaller in tech occupations, which do not require the long and unpredictable hours of workers such as lawyers or doctors, for whom the return on extra hours is much higher.[20] Additionally, it could be that the estimates of the bid gap are a more accurate rendition of the residual pay gap, since I can explain close to 100% of the variations in bids with my controls, leaving little room for omitted variable bias.

5.4 Within- or between-job disparities?

There are two possible explanations for the gap in bid salaries. First, there may be *within-job* bid disparities, that is men and women are offered the same jobs, but women are extended lower bids for these jobs. Alternatively, the gap could come from *between-job* disparities: women, for a given resume, could be offered different, lower-paying jobs. In order to disentangle these channels, I run the same regressions as in Table V but add job fixed effects.

Column (1) of Table VI shows that the raw bid gap within jobs is 4.9%. This estimate is larger than the raw bid gap without job fixed effects from Column (1) of Table V. In other words, in this setting, it is not that women are being offered lower-paying jobs, but rather that, on average, they are offered lower pay for the same job. Once we add resume characteristics (Column (2)), the bid gap narrows to 1.8%. Therefore, for a given job, gender differences in resumes can only explain part of the within-job bid gap. Column (3) adds only the ask salary and the pay gap goes down to 0.6%. Finally, adding resume characteristics and the ask salary reduces the bid gap to a point estimate very close to zero (0.3%). This result indicates that the bid gap does not operate through the composition of jobs for which women interview. Similar results hold when we control for firm fixed effects instead of job fixed effects in Appendix Table C.11.

Resume characteristics, such as experience, determine the type of jobs (and corresponding salary

[20] Mas and Pallais (2017) also highlighted the fact that women, particularly those with young children, have a higher willingness to pay to work from home and to avoid employer scheduling discretion.

range) that individuals are selected for, but within jobs they play a minor role in the determination of pay. This is illustrated by the evolution of the adjusted R^2 in the bid gap regression: while resume characteristics explain more than 80% of the total variation in the regressions without job fixed-effects (Table V Column (2)), they can only explain 28% of the total variation within jobs in Table VI Column (2). In addition, solely using the ask salary as a control in the regression with job fixed effects boosts the adjusted R^2 to 0.81 (Table VI Column (3)). Finally, adding the resume characteristics to the ask salary only marginally increases the adjusted R^2 to 0.82 in Column (4) of Table VI. Taken together, these results indicate that, for a given job, the ask salary plays a much larger role in the determination of the bids than resume characteristics. This is confirmed by the point estimate on the log ask salary: even within jobs and after controlling for all resume characteristics, a 1% increase in the ask salary is associated with a 0.77% increase in the bid salary.

5.5 Final offers: results

Given that bid salaries are non-binding, one may worry that the bid gap is not a relevant measure for the actual gender pay gap. To address this concern, Table VII presents results on the final offer gap for the restricted sample of candidates that are hired by a company. The left-hand side variable is now $Log(Final_{ib})$, the salary at which candidate i was hired for the job corresponding to bid b. The right-hand side variables are the exact same as in Table V. The sample of final offers is much smaller than the sample of interview requests (463,869 interview requests were sent out and there were 7,582 final offers) but the point estimates are qualitatively similar. The raw final offer gap is 5.1% (Column (1)) and controlling for resume information leaves a significant 1.4% gap (Column (2)). After adding the ask salary to the resume controls, as in Column (5) of Table VII, I find a point estimate for the gender pay gap that is close to zero (-0.9%). These results are insensitive to the addition of firm fixed effects in Columns (6) to (8). Indeed, the final offer gap remains significant, at 1.8%, when controlling for resume characteristics as well firm fixed effects, but not the ask salary, and becomes insignificant when adding the ask salary to the controls. Additionally, the interaction coefficient between the female dummy and the log ask salary (in Column (5) without firm fixed effects and Column (8) with firm fixed effects) is again essentially zero.

5.6 Additional results and robustness checks

The effect of introducing the ask salary on other controls: Introducing the ask salary as a control in Table V Column (4) brings the coefficient on the female dummy to zero. Is this result unique to the female dummy or does introducing the ask salary impact other coefficients? To answer this question, Appendix Table C.5 reports the coefficients on some of the other controls in the gender bid and final gap regressions. Specifically, Column (4) reports the coefficients on education, experience, and employment before adding the ask salary to explain the bid gap and Column (5) reports them after adding it. Column (7) and (8) do the same exercise for the final offer gap. The coefficient on the female dummy is not the only coefficient that shrinks essentially to zero when adding the ask salary as a control. For example, the coefficient on the employed dummy falls from 0.045 to 0.003 for the bid and from 0.032 to .007 for the final salary, and the magnitude of the coefficients' decrease is similar for education. The coefficients on dummies for years of experience also decrease although some remain positive. For instance, the coefficient on 15+ years of experience falls from 0.29 to 0.03 for the bid and 0.04 for the final salary. The results for the final offer gap in Column (3) and (4) are qualitatively similar.

To formally test whether the controls still have explanatory power in the deviations of the bid from the ask salary, Table C.7 Column (1) runs the difference between *Log*(Bid salary) and *Log*(Ask salary) on the same controls, while Column (2) repeats the same exercise with the difference between *Log*(Final salary) and *Log*(Ask salary).[21] In both columns, the experience variables have significant coefficients but the R-squared is very low (0.021 in Col (1) and 0.047 in Col (2)). Interestingly, the coefficient on female in Col (2) is positive and significant (0.018), suggesting that companies partially correct for women's lower initial asks in their final offers.

Sensitivity analysis: In Table V, the impact of the ask salary on the bid gap is estimated on the full sample of bids sent out by companies. However, only a sub-sample of the underlying jobs lead to a final hire. One may argue that only the bids from firms that end up hiring on the platform should be considered, since other firms may not be putting as much effort into their search and bid decisions. To address this concern, in Table C.12, I re-run the same regressions as in Table V but only keep the bids for jobs with a final hire. That corresponds to 43% of the total number of bids. The results are essentially the same as in Table V.

Another hypothesis is that there may be two types of firms: the ones that default to the candidate's ask and the ones that price the job rather than the candidate. To test this idea, in Table C.13, I re-run the same regressions from Table V but on the subset of bids that are different from the ask, which represents 25% of the data. While the results on that sub-sample are qualitatively similar to Table V, the magnitudes vary somewhat in the direction predicted by the

[21] This is equivalent to constraining the coefficient on *Log*(Ask salary) to equal one in Table C.5

hypothesis. Indeed, the raw bid gap on that sub-sample is 4.1%, the adjusted gap is 1.6%, and adding the log ask salary narrows it further to 0.3%. In other words, for companies that do not default to the candidate's ask, the candidate's resume explains more of the raw bid gap (60% vs. 40% on the full sample) but the gap remains large and significant, and adding the ask salary still narrows the bid gap significantly.[22]

Updaters analysis: Candidates have the opportunity to update the ask salary displayed on their profile at any time during their spell. Spells on the platform usually only last two weeks, but 7.4% of the candidates still update their ask salary within a spell. Therefore, we can observe, for a given candidate, how bids change when the candidate updates his or her ask salary. Table C.15 reports the results of a regression of the log bid salary on the log ask salary with individual spell fixed effects, restricting the sample to people who update during a given spell.

It is important to acknowledge that this analysis suffers from a selection problem: candidates do not decide to update at random. In particular, candidates who raise their ask wage may be reacting to high demand from companies, while candidates updating downwards may be reacting to low demand. This is evident from the gap in offers before the update: candidates who update upwards already have on average seven bids before they update, compared to four for the ones who update downwards, and the average spread between their ask salary and bid salary, before the update, is \$-1,164, compared to \$-6,306 for the ones who update downwards. However, the exercise can still be informative, as one can read the coefficient on the log ask salary in this context as a lower bound for the true effect of the ask on the bid, since previous bids already partially adjusted for the quality of the candidate. Keeping that in mind, a coefficient of 0.48 (Column (1)) is still significantly positive and economically meaningful, although it remains lower than the 0.85 estimate in Table V Column (4). When splitting the sample, we find that there is an asymmetry: bids increase more when the candidate updates upward (the coefficient on the log ask salary is 0.54 in Column (3)) than when he or she updates downward (the coefficient on the log ask salary is 0.40 in Column (5)). It may seem a priori counter-intuitive that candidates gain more when they increase their ask than they lose when they decrease it. The selection issue can explain this phenomenon: candidates updating downward are reacting to a lack of demand and bids lower than their ask, while candidates updating upward are reacting to a high demand, yet they were, on average, not receiving bids higher than their ask before their update.

[22] Table C.14 reproduces this exercise with final offers as the left-hand variable and obtains qualitatively similar results.

5.7 Racial gap

When creating their profiles, candidates are invited to disclose their race. This is done on a voluntary basis and is not displayed on the profile that companies see.[23] 27.6% of the sample (i.e., about 31,200 candidates) decided to report their race. In this sub-sample, 48.3% are White, 40.1% are Asian, 4.6% are African American, and 7.4% are Hispanic.[24]

Column (1) of Table C.16 reports estimates of the raw ask gap and Column (2) reports estimates of the adjusted race ask gap. Once we control for resume characteristics, there is a small ask gap between candidates who identify as White and candidates who identify as Asian(1.0%), African American (1.2%) or Hispanic (1.4%). Column (3) provides estimates of the raw race bid gap and Column (4) provides the adjusted race bid gap. Resume characteristics can explain the majority of the race bid gap. The gap between White and other races is insignificant and highest for African American at 0.4%. Adding the log ask salary as a control in Column (6) brings all coefficients (on race and gender) further down to zero. Similar to the gender bid gap, the coefficient on the interaction between race variables and the log ask salary in Column (7) is insignificant for all race variables. Columns (8) to (12) provide estimates of the gap in final offers by race. Despite noisier estimates, the analysis is, for the most part, similar to the gender final offer gap: the resume characteristics in Column (9) can only explain part of the raw final offer gap of Column (8), while adding the ask salary as a control in Column (11) brings the final offer gap close to zero for most, but not all, races. In particular, Hispanics stand out with a 2.1% final offer gap, even after controlling for the ask salary. Another notable difference is the large, although imprecise, coefficient on African American (-0.044) and the interaction term between African American and the log ask salary in Column (12) (-0.237), suggesting that candidates who self-report being African American are getting lower final returns to asking for more than White candidates do.

These results are suggestive of a larger role for the ask gap, not only in women's salary determination but more broadly in minority groups' negotiations. However, self-selection into the sample that declares race and noisier estimates due to the restricted sample size prevent me from drawing definitive conclusions.

[23] Candidates also have the option to upload a picture of themselves, from which companies can make racial inferences.
[24] This sums to 100.4% instead of 100% because a few candidates in the sample declared more than one race.

6 Gender differences at the extensive margin

So far, we have explored differences in salary offers between men and women. These differences are computed on the sub-sample of individuals who get an interview request and/or a final offer. But this is not the only dimension of gender differences in labor search. In particular, women could be discriminated against at the extensive margin, i.e. there could be gender differences in firms' likelihood to send an interview request or to hire a candidate. In this section, I show that, conditional on their resume characteristics, women in fact get slightly more interview requests than men and, conditional on interviewing, women are just as likely as men to get a final offer.

6.1 Selection into the interview pool

Table VIII explores whether there are gender differences in the number of bids received during a spell.[25] In Column (1), I regress the number of bids received on a female dummy. Since the number of bids is count data, I also report the Average Marginal Effect (AME) in a Poisson regression on the female dummy at the bottom of each column. The coefficient is significantly negative: women receive about half an offer less than men. However, when adding candidates' resume characteristics in Column (2), the coefficient on the female dummy flips and becomes small but significantly positive: women get on average 0.2 offers more than men. The fact that the coefficient changed significantly from Column (1) to Column (2) is mainly due to differences in the type of jobs that candidates of different genders are looking for: software engineering jobs, where there is a much higher concentration of men than women, are also the jobs that make a larger number of bids on average. One could think that women are getting more bids because they are asking for less. However, Column (3) shows that adding the ask salary to the controls does not impact the coefficient on the female dummy much and, if anything, the coefficient is larger with the ask salary control.

6.2 The ask salary as a signal of quality

Column (3) of Table VIII also shows that the ask salary has a small yet positive association with the number of interview requests received. This result may seem a priori surprising: for a given resume,

[25] Observations here are at the spell level rather than the candidate level. That is, if a candidate used the platform several times over the sample period, each spell is accounted for separately. The candidate controls are the same as in the ask salary estimations (Table III Column (6)), except that I add a control for the length of the spell, which varies between 2 and 6 weeks.

candidates who ask for more are, on average, facing higher demand. However, the coefficient on the square of the ask salary is negative (Column (4)). In other words, candidates cannot ask for infinitely more and face ever-growing demand: there is an inflection point after which a higher ask decreases the number of bids that they receive. Finally, Column (5) adds an interaction between the female dummy and the ask salary. The point estimate is insignificant and essentially zero. At the extensive margin, it is not the case that women are penalized or rewarded more than men for asking for more.

To better understand the nature of the relationship between the ask salary and the number of bids received, Figure VII provides a binned scatter plot of the number of bids received against the residual of the ask salary on resume characteristics. We observe a bell-shape relationship between the unexplained component of the log ask salary and the number of bids received. For residual log ask salaries between -0.7 and 0.15, the number of bids received increases with the residual ask salary. Beyond 0.15, the relationship becomes negative, that is asking for more is associated with a lower number of bids received.

A final piece of evidence on the relationship between the ask salary of candidates and the behavior of firms leverages a new methodology developed in Roussille and Scuderi (2022) to infer candidates' preferences over firms by aggregating interview acceptance and rejection decisions. The utility afforded by an interview request made by firm j to candidate i with bid salary b_{ij} is modelled as as the sum of monetary/wage and non-wage components:

$$V_{ij} = \underbrace{u_i(b_{ij})}_{\text{monetary comp.}} + \underbrace{\Xi_{ij}}_{\text{non-wage amenities}}$$

. The non-wage component of utility is assumed to be the sum of a systematic component A_j and an idiosyncratic component ξ_{ij},

$$\Xi_{ij} = A_j + \xi_{ij},$$

where $\xi_{ij} \overset{iid}{\sim} EV_1$. A_j reflects the component of valuations over firm j's non-wage amenities that is shared across all candidates, while ξ_{ij} reflects idiosyncratic differences in those valuations. For instance, differences in A_j might reflect whether firm j's offices are located in a more or less desirable location, while differences in ξ_{ij} might reflect whether candidate i's commute to firm j would be relatively long or short. Estimates of A_j are constructed by isolating a set of interview acceptances and rejections for which candidates' revealed preferences may be cleanly inferred. In particular, suppose candidate i has offers from both firms j and k *at the same bid salary*. If i accepts j's interview request, but rejects k's interview request, we may infer:

$$A_j - A_k \geq \xi_{ik} - \xi_{ij}.$$

Roussille and Scuderi (2022) builds on Sorkin 2018 to develop a maximum likelihood procedure to estimate the mean non-wage amenity value of each firm, A_j, by aggregating these revealed preference inequalities. For the purposes of the analysis here, the estimated amenity values are converted into percentile ranks, where those ranks are increasing in the estimated non-wage amenity value A_j.

Table C.10 reports regressions that predict the quality of bids and final offers received by candidates, as proxied by firms' estimated rankings, as a function of candidate gender and ask salary. All regressions include month-by-year fixed effects. Column (1) illustrates that unconditionally, women receive bids from firms with somewhat worse amenities than men: the coefficient on the female dummy is roughly -1.8. This unconditional relationship also holds true for final offers (Column (4)). Adding the full set of resume controls, however, essentially eliminates differences between men and women in the quality of the bids (Column (2)) and final offers (Column (5)) they receive. Indeed, additionally controlling for the ask salary actually reverses the gap: conditional on the ask (plus other resume characteristics), women receive bids from firms with slightly better amenities than men, although the coefficient on the female dummy is not statistically significant. Even more starkly, the gap in the amenity values of final offers is completely reversed (Column (6)): unconditionally, women receive final offers from firms ranked 1.24 percentiles lower than men, but conditional on ask, women receive bids from firms ranked 1.22 percentiles *higher* than men. Interestingly, the coefficient on the ask salary is significantly positive, indicating that, for a given resume, candidates with a higher ask salary receive offers from better ranked firms.

The existence of an upward sloping range in the relationship between the residual ask salary and the number of interview requests received as well as the fact that candidates with a higher residual ask are interviewed by better ranked firms can be explained by the following idea: firms interpret the residual ask salary as a signal of unobserved quality. When deciding whether to send an interview request to a candidate, the firm considers the trade-off between the final salary it will have to pay the candidate and the expected return to the match. For a given set of resume characteristics, this expected return to the match is increasing in the quality of the candidate. While the firm cannot directly observe this quality before interviewing the candidate, the ask salary sends a positive signal about this quality. The ask salary therefore plays an ambiguous role in the decision of the firm to interview the candidate. On the one hand, firms predict that a higher ask salary leads to a higher final salary cost to the firm. On the other hand, a higher ask salary is a signal of unobserved quality and therefore a higher return to the match. The relative size of these effects determines the sign of the relationship between the ask salary and the probability of getting an interview request from any given firm.

The idea of price as a signal of quality, while under-studied in the context of wage bargaining, has been theorized for consumer products in the fields of IO and game theory. Seminal papers in this literature (Wolinsky (1983), Milgrom and Roberts (1986)) study conditions under which product price or some combination of price and another quality signal, such as advertising, can effectively signal product quality when consumers are not fully informed. In addition, recent experimental evidence in Agan, Cowgill, and L. Gee (2021) corroborate the idea that salaries can be interpreted by recruiters as a signal of quality. Indeed, in a wage-setting experiment analyzing the effect of salary histories, they show that recruiters' beliefs on candidates' quality increase with higher disclosed wages, conditional on having the same resume.

In Appendix Section A, adapting Wolinsky (1983)'s model to the labor market, I propose a framework to explain how, in a context of imperfect information about a candidate, a separating equilibrium in which the candidate's ask salary is a signal of their quality can exist. The intuition for the equilibrium in this model can be summarized as follows. At a given ask salary, firms expect a certain unobserved quality of the candidate. A candidate that asks for a given salary may be of lower quality, but information revealed during the interview will enable some potential firms to find this out, and provided there are competing candidates, they will not hire this one. Therefore, in deciding whether to ask for a higher salary than what the firm expects given her quality, the candidate weighs the decrease in his chances of being hired against the gain in salary in the event they get an offer. If the chances of detection are large enough to outweigh the potential salary gains, it is best for the candidate to signal his true quality with his ask salary.

Firms differ in the candidates' quality-ask combination that maximises their expected profit. I model this as firms having a different match-productivity parameter: the match with a high quality candidate has a higher return to the firm if the job involves complex tasks. In equilibrium, candidates receive interview requests from their ideal firm type, that is the type that is willing to pay them the most for their quality. Therefore, whether a higher candidate's ask salary is associated with more or less interview requests entirely depends on the empirical distribution of firm types on the platform. As explained in the model section A.5, we can approximate a given firm type by estimating the range of residual ask salaries that it interviews in. Figure A.2 shows this relationship is also bell-shaped, providing further theoretical foundations to my empirical findings.

In this model, women have downward biased beliefs about the salary they can ask for that stems from inaccurate information about the equilibrium. However, firms do not learn about these biases because interviews go equally well for men and women. This feature of the model comes from the signal design: it can only provide firms with a "red flag", that is whether the candidate is below her expected quality. But, in equilibrium, neither men nor women end up raising this flag.

6.3 Selection into the final offer pool

We now turn to testing whether, after an interview, firms are more or less likely to give the job to a comparable man or woman. In Table IX, the dependent variable is a dummy equal to 1 if a candidate was offered the job for which they interviewed. The raw gender gap in the probability of getting a final offer after interviewing is insignificant (Column (1)), and neither adding the candidate's resume characteristics (Column (2)) as well as his or her ask salary (Column (3)) nor including job FE (Column (4)) affects this result. In a nutshell, conditional on interviewing, women are just as likely as men to get the job.

Going back to the evidence in Table VIII that, for a given resume and ask salary, women receive more bids than men, two interpretations are possible. The first one is that, for a given resume and ask salary, firms believe that women have a higher unobserved quality. However, the fact that, conditional on interviewing, women are not more likely than men to get an offer seems to invalidate this story. Another possibility is that some tech companies practice affirmative action and are actively interviewing women in order to address the gender imbalance in the industry.

7 Closing the gap

In mid-2018, a change on the platform affected the way some candidates were prompted to report their ask salary. Specifically, before the reform, the ask salary was an empty field. After the reform, the field was pre-filled with the median of the bid salary for a comparable candidate on the platform. Focusing on San Francisco software engineers, I show that this change drove the ask gap from 2.9% to -0.6% and similarly drove the bid gap from 2.5% to -0.3%. This effect is driven by women asking for more than they did before the reform, rather than men asking for less.

7.1 Description of the reform

To create their profiles, candidates have to answer the question: "what base salary are you looking for in your next role?". This is what I have referred to as the ask salary. From the first year of the data to mid-2018, the answer box for this question was an empty text entry. Starting in mid-2018, the answer box was pre-filled with the median bid salary on the platform over the past 12 months. The median that is shown to the candidate is specific to his or her combination of desired location, job title, and experience in that job. The change is illustrated in Figure IX with a screenshot of the ask salary elicitation web page before and after the reform. This change was motivated by the belief at Hired.com that the platform should provide candidates with a more transparent experience. Even before the reform, candidates could see a histogram of the salaries on the platform. However, the information was somewhat hard to interpret from the histogram since no scale was indicated on the y-axis, neither the median nor the mean were provided and, more substantially, the histogram bins were wide ($10,000) and therefore did not provide very detailed information on salary choices. The change affected candidates who were either creating or updating a profile. The histogram and median salary were displayed only if Hired.com had enough data to make the calculations for the candidate's combination of desired location, job title, and experience in that job. Unfortunately, the platform did not track what the threshold for computing the histogram and median was, so I cannot construct a control group for whom the information wasn't shown. However, because San Francisco software engineer roles are the largest group (25% of the data has this single combination of occupation and location), I received confirmation that this population was fully treated. Therefore, the analysis focuses on San Francisco software engineer roles, comparing candidates who created or updated a profile before and after the reform. Finally, the reform was not anticipated by either the candidates or the firms. Indeed, the company did not advertise externally about the feature change and therefore new candidates were not drawn to the platform by the feature change. In addition, given that the feature only impacted the candidates' experience on the platform, the firms were not informed of this change at the time it was implemented.

7.2 Empirical strategy and identification assumptions

My main empirical strategy compares individuals who created a profile before the change and after the change. I first explore the effect of the reform on the ask salary of men and women, as well as on the ask gap. I follow the literature on Interrupted Time Series (ITS) designs by estimating:

$$Log(Ask_i) = \alpha + \beta_0 After_t + \beta_1 Female_i + \beta_2 Female_i \times After_t + \beta_3 X_i + \gamma_t + \epsilon_i \tag{8}$$

where $t = t(i)$ is the month in which candidate i created his or her profile, $After_t$ is a dummy equal to 1 after the feature change, $Female_i$ is equal to 1 if the candidate is female, and X_i includes the candidate profile controls. γ_t includes a month FE (1 to 12) to capture seasonal effects and a linear time trend (t) to capture the growth of the platform over time. $Log(Ask_i)$ is measured at the beginning of the spell, that is at the time the candidate created the profile. β_0 estimates the effect of the reform on the male ask salary and $\beta_0 + \beta_2$ estimates the effect of the reform on the female ask salary. β_1 estimates the ask gap before the reform while $\beta_1 + \beta_2$ estimates the ask gap after the reform.

Second, I investigate the effect of the reform on the bid salaries sent by firms in equation 9:

$$Log(Bid_{ib}) = \alpha + \beta_0 After_t + \beta_1 Female_i + \beta_2 Female_i \times After_t + \beta_3 X_{ib} + \gamma_t + \epsilon_{ib} \tag{9}$$

The controls here are the same as in Equation 8, except X_{ib} can now contain $Log(Ask_{ib})$, the ask salary of candidate i when he or she received his or her $b'th$ interview request. The dependent variable is the log of the bid salary sent to candidate i for his or her $b'th$ interview request. Similar to Equation 8, β_0 will document the effect of the reform on bids received by male candidates and $\beta_0 + \beta_2$ will document the effect of the reform on bids received by female candidates. β_1 estimates the bid gap before the reform while $\beta_1 + \beta_2$ estimates the bid gap after the reform. A similar analysis is then run on the final offers.

I then explore several measures of the effect of the reform on the candidate at the extensive margin: the number of bids received by a candidate during a spell k, the time it takes to receive the first bid during a spell k,[26], the likelihood of getting a final offer, as well as the rank of the firms that bids and makes offers to the candidate.

[26] The specification is the same as in Equation 8 except the left side respectively becomes $Nbbids_{ik}$ and $Hours_{ik}$, as defined in Section 6, and we add the length of the candidate spell (2 to 6 weeks) to the controls.

This interrupted time series analysis may be misleading if selection into the platform changed as a result of the reform, in a way that would have led the ask gap after the reform to differ irrespective of the reform. To address this concern, I fit Equation 2[27] in the pre-period to predict the ask salary of every candidate, controlling for all their resume characteristics. I then run this predicted ask against an interacted model of female and after dummies. Results are presented in Table X: the coefficient on the interaction between female and after is exactly zero. In other words, the predicted ask gap is stable across periods. Table C.17 also provides summary statistics on candidates' resume characteristics before and after the change, illustrating the absence of differential selection of men and women onto the platform after the reform.

7.3 Results

Figure X plots the time series of mean ask, bid and final salary for male and female separately, net of a rich set of controls, as in Chetty et al. (2011) and Yagan (2015). Within each month, I first regress the outcome variables on the candidates' resume characteristics. I then construct the two series shown in each subfigure by setting each month's difference between the two lines equal to that month's regression coefficient on the female indicator, and setting the weighted average of that month's data points equal to the month's sample average. The figure shows that the female time series tracked the male time series of ask, bid and final salaries closely in the several months before the feature change, suggesting that the two time series would have continued to evolve in parallel but at significantly different levels in the absence of the feature change. We then observe a clear jump in female ask, bid and final salaries to the level of men's salaries. The narrowing of the gap between the two lines persists several months after the change.

Ask salary: Table XI formalizes the visual evidence in Figure Xa by reporting the estimates of Equation 8. Column (1) shows that, in the pre-reform period, the ask gap was 2.9% (coefficient on the female dummy). In the post period the ask gap, measured as the sum of the coefficient on the female dummy and on the interaction between *Female* and *After*, essentially goes to zero. This evolution in the ask gap is led by women asking for more, rather than by men asking for less. In particular, the reform led women to ask for 4.2% more while men ask for about the same as they would have otherwise.

In line with results from Section 4, the pre-reform gender ask gap is much larger for candidates with more experience: while the ask gap before the reform is 1.5% for candidates with 0-4 years

[27] Except that instead of Month $\times$ Year FE, there are just Month FE (1-12) and a monthly linear time trend.

of experience as a software engineer (Column 3), it rises to 4% for candidates with 4-10 years of experience in this occupation (Column (3)). Strikingly, the effect of the reform is also gradual with experience: women with 0-4 years of experience as a software engineer ask for about the same wages before and after the reform, while women with 4-10 years of experience in this occupation ask for 4% more than before the reform ($\beta_0 + \beta_2$). These changes in women's asks essentially either close or significantly reduce the ask gap for all groups.

Figure B.4 plots the cumulative distribution function of ask salaries for different experience groups separately before the reform (solid lines) and after (dashed lines), for men (on the left) and women (on the right). For a given experience group, all candidates saw the same median. This figure illustrates the experience gradient by gender. For all experience groups, the distribution for men looks very similar pre and post reform. Conversely, for women, the cumulative distribution function shifts to the right, with a larger shift for experience groups with a larger initial ask gap. The figure does not present clear evidence of bunching at a specific salary, suggesting that candidates did not massively resorted to the default setting of the median salary after the reform.[28]

Bid and Final salary: Table XII formalizes the visual evidence in Figures Xb and Xc by reporting the estimates of Equation 9, assessing the effect of the reform on the gender bid gap. Column (1) reports a 2.5% bid gap before the reform. This gap goes to -0.3% ($\beta_1 + \beta_2$) after the reform. This result is driven by the fact that women are offered 2.6% more and men are offered about the same as they would have been offered absent the reform. The experience gradient also manifests itself in the bid gap: for the 0-4 years of experience group (Column (3)), the pre-reform bid gap is small (1.1%), and the reform had little impact on bids extended to women. In contrast, I find that for the group with more than 4 years of experience, the pre-reform bid gap is larger (at 3.1% for 4-10 years of experience and 4.7% for more than 10 years of experience) and the effect of the reform is correspondingly larger (Column (4) and (5)). Controlling for the ask salary in Column (5) narrows the pre- and post-reform bid gaps to small point estimates (respectively 0.004 and 0.000). The results also hold when we add job fixed effects: for a given job, the bid gap was 1.8% before the reform and fell to 0% after the reform (Column (6)). Finally, while under-powered, the analysis on the final salary also suggests that the reform closed the final offer gap (Column

[28] One caveat here is that I cannot measure the exact share of candidates that bunch at the median as a result of the reform. The reason, according to the product designers at Hired.com, is that they used the past 12 months of data to compute the median suggestion but did not actually record in their data what that suggestion was. Therefore, there is a margin of error (for instance, did they really update the suggestion the first day of each month?). With that in mind, using the history of Hired.com data to back out the median, the share that gave exactly the median bid is 10%. The overall variance of the ask salary also did not significantly fall as a result of the reform. Section 7.4 explores the potential mechanisms behind these outcomes.

(7)).

Figure XI plots the effect of the reform on the ask and bid gaps as a function of the pre-reform gaps, separately by experience groups. All dots are close to the 45 degree line, illustrating the fact that the reform had an effect on the bid and ask gap that is proportional to the pre-reform gap.

Other variables: The median salary shown to candidates accounts for the candidate's experience but not for their other resume characteristics (for instance, their education). Therefore, candidates with different education levels but the same experience see the same suggestion. As a consequence, the reform could have impacted the role of other controls in the determination of the ask salary. Table C.18 reports the results of a regression of the log ask salary on all the resume characteristics controls, separately for the pre-reform period (Column (1)) and the post-reform period (Column (2)). Remarkably, the coefficients of the variables used to determine the median (i.e. experience) increase in the post-reform period, while the coefficients of the other controls shown in the table either remain the same or decrease in magnitude.[29]

Extensive margin: We have just shown that asking for more led to higher bids. However, it could be that this positive outcome comes at the expense of other dimensions in the recruitment process. For instance, women could get fewer interview offers as a result of the feature change, or it could decrease their chances of getting a job. The total number of bids received at any given time depends on factors such as the growth of the platform and the demand for software engineers at that time. Therefore, the interrupted time series design is not well-suited to assess the general equilibrium effect of the reform on the total number of bids sent on the platform. However, we can still credibly observe whether the reform had a differential impact on the number of bids received by women, compared to men. To explore this extensive margin response of firms, Table XIII Column (1) predicts the number of bids received by candidates using the female dummy, the after dummy, and their interaction, as well as on the same controls as in Table VIII. The coefficient on the interacted term female $\times$ after is positive and insignificant. Therefore, women did not experience a differential effect of the reform on the number of bids they received, compared to men. Column (2) estimates the number of hours it takes for a candidate to get a first bid. Again, the point estimates for the coefficients on female and female $\times$ after are very small. Column (3) estimates the likelihood of getting an offer on the platform and the point estimates for the coefficients on female and female $\times$ after are close to zero and insignificant. On Columns (4) and (5) I show that

[29] Aside from a few exceptions, this is also true of the variables that are not displayed in the table, such as the 'elite' company (FAANG) dummy.

the reform has not significantly altered the rank of firms that contact women or make them a final offer. Taken together, these results suggest that women face little penalty for demanding wages comparable to men.

7.4 Discussion

The results reported in this section indicate that the new ask salary elicitation framing led women to ask for more and that firms correspondingly bid more on them. Moreover, there is suggestive evidence that women are not penalized, compared to men, at the extensive margin. Two questions arise from these results. On the candidate side, what mechanism could rationalize the fact that the new framing led women to ask for more? On the company side, why is it that firms are not decreasing their demand for female labor, compared to men?

Several reasons can be brought up to explain why women were asking for less in the first place. The fact that the treatment closes the gender ask gap allows me to corroborate some of these reasons and eliminate others. Let us start with the possible explanations for the lower initial female ask salary that do not square with the reform effects. Women could initially have actively been playing a different strategy than men. For instance, one could assume that women put more weight than men on getting a job rather than getting a high salary. This would be in line with experimental evidence that women are more risk-averse than men (see Croson and Gneezy (2009)). Asking for less would then have been aimed at increasing women's chances of getting a job.[30] Alternatively, women could have been trying to signal different unobservables than men, for example the need for more flexible hours or an interest for lower salary / higher social impact jobs. Finally women could be under-confident, or less overconfident than men, about their unobserved ability; therefore believing, for a given resume, that they are worth less than their male counterparts.[31] Under all of these explanations however it seems unlikely that women would have adjusted to the treatment all the way to match men's ask salary. Indeed, if they were knowingly playing a different ask salary strategy than men then differences in ask should have persisted after the treatment.

An alternative set of explanations for why women initially ask for less rely on the idea that, compared to men, women have downward biased beliefs about how much they can ask for. These downward biased beliefs may have had two sources: first, they may be due to biased information

[30] Note that given the empirical relationship between the residual ask salary and the number of interview requests received, this strategy may have been unwarranted.

[31] Contrary to widely shared beliefs, in a Bayesian meta-analysis of overconfidence experiments, Bandiera et al. (2021) cannot reject the hypothesis that gender differences in self-confidence are equal to zero.

about the market wage for their resume, second they may be due to the fact that, despite knowing the median ask salary, women were anticipating discrimination and asked for less to mitigate it. The first source of downward biased belief seems most consistent with the idea that the treatment provided women with more precise information and a nudge to use it. The fact that women with more experience had a larger initial gap and a larger treatment effect reinforces this explanation. Let's assume that to choose their ask salary, candidates rely both on publicly available information and on their informal networks. Further assume that these networks are gender-specific: women have a network that is composed of more women than men do. For junior roles, the variance of salaries is small and the salary information is readily accessible on job boards such as Glassdoor. Therefore, men and women access very similar information. For more senior roles, the variance of salaries is much larger and the estimates provided publicly become less precise. Further, women relying on their informal networks will receive salary information way below what men make for senior roles since the gender pay gap increases with experience. This results in larger ask gaps for senior than junior roles. The treatment then did little to change the information set of junior women but significantly changed the information available - and the incentives to use it - to more senior women. This explanation is consistent with evidence in Dreber, Heikensten, and Säve-Söderbergh (2020). In this paper, the authors run a survey on a representative sample of recent graduates in Sweden data to shed light on the mechanism behind women's lower ask. The paper finds suggestive evidence that beliefs about the wage an ideal candidate would ask for, but not perceived social cost or confidence, can explain most of the 2.5% gender gap in salary requests. A treatment effect on the second source - the fact that women expect discrimination from firms - would have had to go through a more subtle channel: by pre-filling the ask salary answer box, Hired.com sent women a message about their expertise on firms' behavior on the platform. In this scenario, the pre-filling of the ask salary answer box is a signal given by Hired.com that women will not suffer backlash if they ask for more. While I cannot disentangle the salary information / nudge to leverage this information channel from the more subtle channel, it seems unlikely that the latter could entirely explain the closing of the gender ask gap.

Instead of generating bunching at the suggested ask salary, the treatment shifted the entire distribution of ask salaries for women to the right (see Figure B.4). To understand how the treatment could have generated this outcome, we can consider that candidates follow this simple heuristic: they form beliefs about their percentile in the quality distribution, then they make assumptions and/or obtain information about the salaries in their field, and finally choose an ask salary in this distribution that corresponds to their quality percentile. The treatment effect would then be consistent with the idea that women had downward-biased beliefs about the median salary and that treatment corrected it. The provision of information and framing, however, does not shift the variance in their asks, so they still place themselves in the same percentile in the quality distribution.

On the company side, Section 6.2 documented a bell-shape relationship between the (residual) ask salary and the number of bids received and Appendix Section A provides a justification for this empirical finding: the ask salary of candidates is a signal of their unobserved quality. If this pattern indeed reflects a stable structural relationship, the effect of the reform on the number of bids received by women should depend on the distribution of initial asks of the women whose asks were shifted up by the reform. Columns (6) to (8) in Table XIII investigates this hypothesis. First, Column (6) adds the ask salary and ask salary squared to Column (1). This addition pushes the coefficient on the interaction between the Female and After dummy from 0.1690 to 0.037. Therefore, the small estimated increase in the number of bids received by women post reform is entirely explained by their increased ask salary. The dependent variable in Column (7) is the predicted number of bids received using the specification in Column (1) on the pre-period. The coefficient on the interaction between the female and after dummies is zero. This confirms that, aside from their ask salary, women pre and post reform do not differ in their likelihood of getting a bid based on their resume. Finally, the dependent variable in Column (5) is the predicted number of bids received using the specification in Column (3) in the pre-period. The coefficient on the interaction is now 0.178 (positive but insignificant). The fact that this coefficient is between that of Column (1) of that of Column (6) is consistent with the statistical relationship between the number of bids received and the ask salary being structural. Further, this positive coefficient indicates that the women whose ask was shifted up by the reform are in the increasing region of Figure VII, which explains why they do not face a penalty for asking for more.

8 Conclusion

This paper introduces the gender ask gap to the gender pay gap literature. Using novel data from a leading recruitment platform, I document a 2.9% adjusted gender ask gap for a large sample of high-wage workers in the tech industry. This gap is statistically significant and economically meaningful: it represents, on average, $3,493 in annual salary. Remarkably, the 3.7% raw bid gap can entirely be explained by the ask gap: solely controlling for the ask salary, the bid gap falls to

0.2%. Conversely, controlling for the candidates' resume characteristics only narrows the bid gap by 40%. These results qualitatively carry through to the 7,582 final salary offers for the sub-sample of hired candidates. In particular, while resume characteristics can reduce the final offer gap to 1.4%, adding the ask salary to the controls reduces the final offer gap to 0.9%. On this platform, women are not discriminated against at the extensive margin. In particular, conditional on their resume characteristics, women in fact receive slightly more bids than men and, conditional on interviewing, women are just as likely as men to get a final offer. Finally, I show that a change wherein some candidates' ask salary form fields were pre-filled at the median changed the adjusted ask gap from 2.9% to -0.6%, and similarly changed the adjusted bid gap from 2.5% to -0.3%. Yet the number of bids received by women, compared to men, or their likelihood of getting a final offer was not affected. This suggests that there is little penalty to asking for more.

These results were obtained in a context of well-documented labor supply shortages and high levels of competition between employers for qualified workers.[32] Given recent lab-based evidence that cautions against "lean in" recommendations (Exley, Niederle, and Vesterlund (2020)), a better understanding of the contexts and conditions under which asking for more benefits, rather than harms, women is an important avenue for future research.

[32] The unemployment rate of U.S. tech Workers had hit a record low in the study period: The Unemployment Rate for U.S. Tech workers Just Hit the Lowest Number Ever Recorded.

References

Abraham, Katharine G., John C. Haltiwanger, Kristin Sandusky, and James R. Spletzer. 2018. "Measuring the Gig Economy: Current Knowledge and Open Issues." *NBER Working Paper No. 24950.*

Abraham, Lisa, and Alison Stein. 2020. "Words Matter: Experimental Evidence from Job Applications." *Working Paper.*

Agan, Amanda, Bo Cowgill, and Laura Gee. 2021. "Salary History and Employer Demand: Evidence from a Two-Sided Audit." *Working paper.*

Agan, Amanda, Bo Cowgill, and Laura Katherine Gee. 2020. "Do Workers Comply with Salary History Bans? A Survey on Voluntary Disclosure, Adverse Selection, and Unraveling." *AEA Papers and Proceedings* 110 (May): 215–19.

Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber. 2005. "Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools." *Journal of Political Economy* 113 (1): 151–184.

Babcock, Linda, and Sara Laschever. 2006. *Why Women Don't Ask: The High Cost of Avoiding Negotiation and Positive Strategies for Change.* Bantam.

Babcock, Linda, Sara Laschever, Michele Gelfand, and Deborah Small. 2003. "Nice Girls Don't Ask." *Harvard Business Review.*

Baker, Michael, Yosh Halberstam, Kory Kroft, Alexandre Mas, and Derek Messacar. 2019. "Pay Transparency and the Gender Gap." *NBER Working Paper* 25834.

Bandiera, Oriana, Nidhi Parekh, Barbara Petrongolo, and Michelle Rao. 2021. *Men are from Mars, and women too: a Bayesian meta-analysis of overconfidence experiments.* Economics Series Working Papers 957. University of Oxford, Department of Economics.

Barach, Moshe A., and John J. Horton. 2021. "How Do Employers Use Compensation History? Evidence from a Field Experiment." *Journal of Labor Economics* 39 (1): 193–218.

Barefoot, Kevin, Dave Curtis, William Jolliff, Jessica R. Nicholson, and Robert Omohundro. 2018. "Trends in the Information Technology sector." *BEA Working Paper.*

Bennedsen, Morten, Elena Simintzi, Margarita Tsoutsoura, and Daniel Wolfenzon. 2019. "Do firms respond to gender pay gap transparency?" *NBER Working Paper* 25435.

Bergerhoff, Jan, Lukas Kiessling, Pia Pinger, and Philipp Seegers. 2019. "Gender Differences in Wage Expectations: Sorting, Children, and Negotiation Styles." *IZA, Discussion paper, No. 12522.*

Bertrand, Marianne. 2017. "The Glass Ceiling." *Coase Lecture, London School of Economics, March 2017.*

Biasi, Barbara, and Heather Sarsons. 2020. "Flexible Wages, Bargaining, and the Gender Gap." *Working paper.*

Blau, Francine D., and Lawrence M. Kahn. 2017. "The Gender Wage Gap: Extent, Trends, and Explanations." *Journal of Economic Literature* 55(3):789–865.

Boudreau, Kevin, and Nilam Kaushik. 2020. "The Gender Gap in Tech and Competitive Work Environments? Field Experimental Evidence from an Internet-of-Things Product Development Platform." *NBER Working Papers* 27154.

Bowles, Hannah Riley, Linda Babcock, and Kathleen L. McGinn. 2005. "Constraints and triggers: Situational mechanics of gender in negotiation." *Journal of Personality and Social Psychology* 89(6):951–965.

Caldwell, Sydnee, and Emily Oehlsen. 2018. "Monopsony and the Gender Wage Gap: Experimental Evidence from the Gig Economy." *Working paper.*

Chamberlain, Andrew, and Jyotsna Jayaraman. 2017. "The Pipeline Problem: How College Majors Contribute to the Gender Pay Gap." *Glassdoor Economic Research.*

Chamberlain, Andrew, Daniel Zhao, and Amanda Stansell. 2019. "Progress on the Gender Pay Gap: 2019." *Glassdoor Economic Research.*

Chen, Shuowen, Victor Chernozhukov, Ivàn Fernàndez-Val, and Ye Luo. 2019. *Sorted Effects: Sorted Causal Effects in R.* arXiv: 1909.00836 [econ.EM].

Chernozhukov, Victor, Ivàn Fernàndez, and Ye Luo. 2018. "The Sorted Effects Method: Discovering Heterogeneous Effects Beyond Their Averages." *Econometrica* 86 (6): 1911–1938.

Chetty, Raj, John N. Friedman, Emmanuel Saez Nathaniel Hilger, Diane Whitmore Schanzenbach, and Danny Yagan. 2011. "How Does Your Kindergarten Classroom Affect Your Earnings? Evidence from Project STAR." *Quarterly Journal of Economics* 126(4):1593–1660.

Chetty, Raj, John N. Friedman, Emmanuel Saez, Nicholas Turner, and Danny Yagan. 2017. "Mobility Report Cards: The Role of Colleges in Intergenerational Mobility." *NBER Working Paper* 23618.

Cook, Cody, Rebecca Diamond, Jonathan Hall, John A. List, and Paul Oyer. 2018. "The Gender Earnings Gap in the Gig Economy: Evidence from over a Million Rideshare Drivers." *Stanford GSB Working paper No. 3637.*

Cortés, Patricia, Jessica Pan, Laura Pilossoph, and Basit Zafar. 2021. "Gender Differences in Job Search and the Earnings Gap: Evidence from Business Majors." *NBER Working Paper 28820.*

Croson, Rachel, and Uri Gneezy. 2009. "Gender Differences in Preferences." *Journal of Economic Literature* 47(2):448–474.

Cullen, Zoey, and Bobak Pakzad-Hurson. 2020. "Equilibrium Effects of Pay Transparency in a Simple Labor Market." *Working Paper.*

Dreber, Anna, Emma Heikensten, and Jenny Säve-Söderbergh. 2020. *Why do Women Ask for Less?* SSRN Scholarly Paper. Social Science Research Network, October. doi:10.2139/ssrn.,WhydoWomenAskforLess?(October2,2020).10.2139/ssrn.3703813.

Exley, Christine L., Muriel Niederle, and Lise Vesterlund. 2020. "Knowing When to Ask: The Cost of Leaning In." *Journal of Political Economy* 128(3):816–854.

Fluchtmann, Jonas, Anita Glenny, Nikolaj Harmon, and Jonas Maibom. 2020. "The Gender Application Gap: Do men and women apply for the same jobs?" *Working Paper.*

Garbinti, Bertrand, Jonathan Goupille-Lebret, and Thomas Piketty. 2018. "Income inequality in France, 1900-2014: Evidence from Distributional National Accounts (DINA)." *Journal of Public Economics* 162:63–77.

Gee, Laura K. 2019. "The More You Know: Information Effects on Job Application Rates in a Large Field Experiment." *Management Science* 65 (5): 2077–2094.

Goldin, Claudia. 2014. "A Grand Gender Convergence: Its Last Chapter." *American Economic Review* 104(4):1091–1119.

Goldin, Claudia, Sari Pekkala Kerr, Claudia Olivetti, and Erling Barth. 2017. "The Expanding Gender Earnings Gap: Evidence from the LEHD-2000 Census." *American Economic Review: Papers and Proceedings* 107(5):110–114.

Goldin, Claudia, and Cecilia Rouse. 2000. "Orchestrating Impartiality: The Impact Of 'Blind' Auditions On Female Musicians." *American Economic Review* 90(4):715–741.

Gomez-Herrera, Estrella, and Frank Mueller-Langer. 2019. "Is There a Gender Wage Gap in Online Labor Markets? Evidence from Over 250,000 Projects and 2.5 Million Wage Bill Proposals." *Working paper.*

Kerr, William R, and Frédéric Robert-Nicoud. 2020. "Tech Clusters." *NBER Working Paper* 27421.

Kleven, Henrik, Camille Landais, and Jakob Egholt Søgaard. 2019. "Children and Gender Inequality: Evidence from Denmark." *American Economic Journal: Applied Economics* 11(4)):181–209.

Krueger, Alan B., and Andreas I. Mueller. 2016. "A Contribution to the Empirics of Reservation Wages." *American Economic Journal: Economic Policy* 8:142–79.

Kuhn, Peter J., and Kailing Shen. 2013. "Gender Discrimination in Job Ads: Theory and Evidence." *Quarterly Journal of Economics* 128 (1):287–336.

Kuhn, Peter, Kailing Shen, and Shuo Zhang. 2019. "Gender-Targeted Job Ads in the Recruitment Process: Evidence from China." *NBER Working Paper* 25365.

Le Barbanchon, Thomas, Roland Rathelot, and Alexandra Roulet. 2021. "Gender Differences in Job Search: Trading off Commute against Wage*." *The Quarterly Journal of Economics* 136 (1): 381–426.

Leibbrandt, Andreas, and John A. List. 2015. "Do Women Avoid Salary Negotiations? Evidence from a Large-Scale Natural Field Experiment." *Management Science* 61(9):2016–2024.

Litman, Leib, Jonathan Robinson, Zohn Rosen, Cheskie Rosenzweig, Joshua Waxman, and Lisa M. Bates. 2020. "The persistence of pay inequality: The gender pay gap in an anonymous online labor market." *PLoS ONE* 15(2).

Marinescu, Ioana Elena, and Daphné Skandalis. 2019. "Unemployment Insurance and Job Search Behavior." *Quarterly Journal of Economics* Conditionally accepted.

Mas, Alexandre, and Amanda Pallais. 2017. "Valuing Alternative Work Arrangements." NBER Working Paper 22708, *American Economic Review* 107 (12): 3722–3759.

Milgrom, Paul, and John Roberts. 1986. "Price and Advertising Signals of Product Quality." *Journal of Political Economy* 94 (4): 796–821.

Murciano-Goroff, Raviv. 2018. "Missing Women in Tech: The Labor Market for Highly Skilled Software Engineers." *Working Paper.*

Neumark, David. 2004. "Sex Differences in Labor Markets." *Routledge* 111(3):1–416.

———. 2018. "Experimental Research on Labor Market Discrimination." *Journal of Economic Literature* 56(3):799–866.

O'Neill, June, and Dave O'Neill. 2006. "What Do Wage Differentials Tell Us about Labor Market Discrimination?" *The Economics of Immigration and Social Policy* 24:293–357.

Olivetti, Claudia, and Barbara Petrongolo. 2016. "The Evolution of Gender Gaps in Industrialized Countries." *Annual Review of Economics* 8(1):405–434.

Reuben, Ernesto, Matthew Wiswall, and Basit Zafar. 2017. "Preferences and Biases in Educational Choices and Labour Market Expectations: Shrinking the Black Box of Gender." *The Economic Journal* 127:2153–2186.

Rich, Judith. 2014. "What Do Field Experiments of Discrimination in Markets Tell Us? A Meta Analysis of Studies Conducted Since 2000." *IZA Discussion Paper* 8584:1–71.

Rigdon, Mary L. 2012. *An Experimental Investigation of Gender Differences in Wage Negotiations.* SSRN Scholarly Paper. Social Science Research Network, October. doi:10.2139/ssrn.2165253.

Roussille, Nina, and Benjamin Scuderi. 2022. "Bidding for Talent: Equilibrium Wage Dispersion on a High-Wage Online Job Board." *Working paper.*

Small, Deborah, Michele Gelfand, Linda Babcock, and Hilary Gettman. 2007. "Who Goes to the Bargaining Table? The Influence of Gender and Framing on the Initiation of Negotiation." *Journal of Personality and Social Psychology* 93(4):600–13.

Sorkin, Isaac. 2018. "Ranking Firms Using Revealed Preference." *The Quarterly Journal of Economics* 133 (3): 1331–1393.

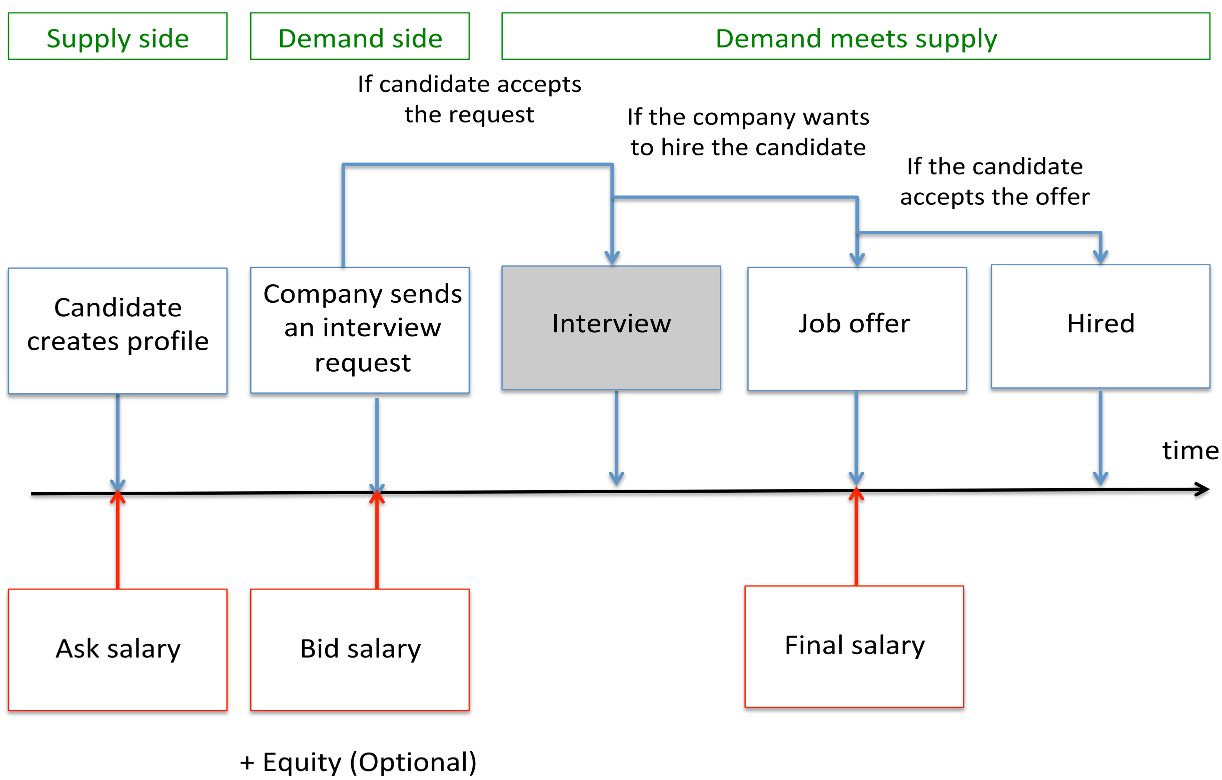
Visier and Insights. 2017. "The Truth About Ageism in the Tech Industry." *Report.*

Wolinsky, Asher. 1983. "Prices as Signals of Product Quality." *Review of Economic Studies* 50 (4): 647–658.

Yagan, Danny. 2015. "Capital Tax Reform and the Real Economy: The Effects of the 2003 Dividend Tax Cut." *American Economic Review, lead article* 105(12):3531–3563.

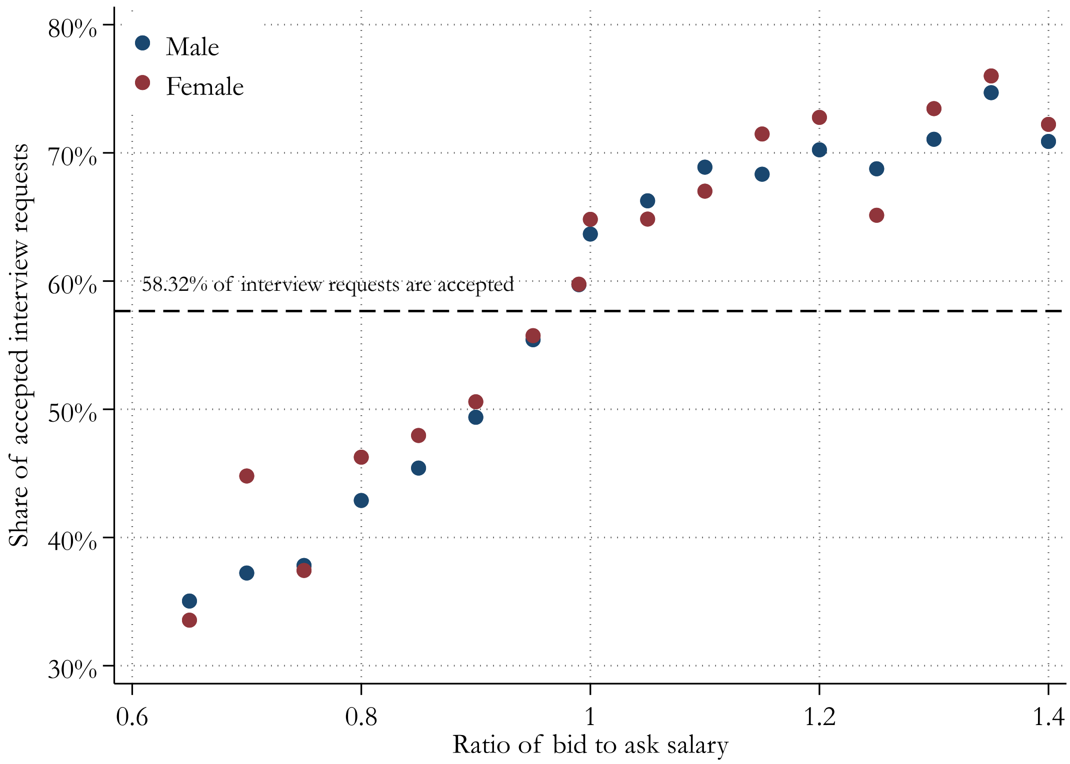
Figures

Figure I: Timeline of the recruitment process on Hired.com



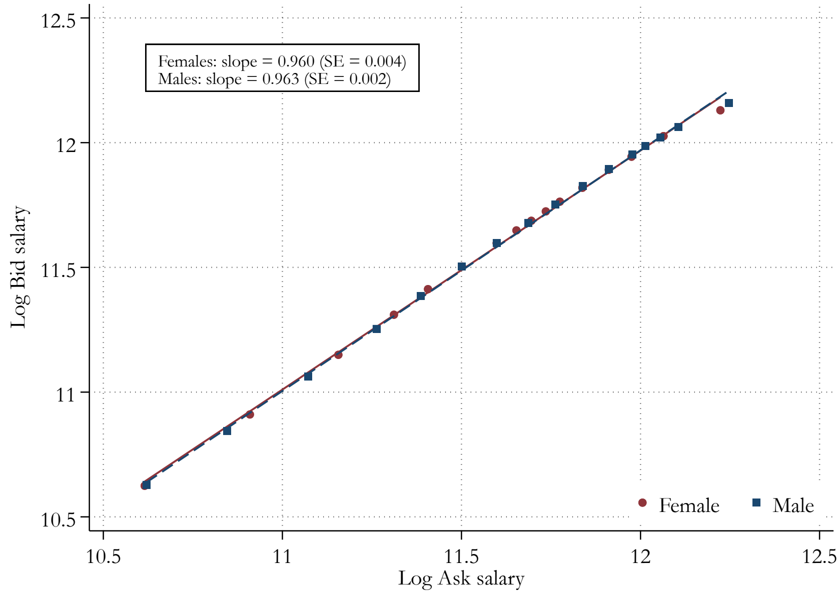
Note: This figure shows the timeline of a recruitment on Hired.com. In red boxes are the different salaries that are captured on the platform. The blue boxes describe all the steps of a recruitment on the platform, from profile creation to hiring. The grey shading for the interview stage indicates that I do not have meta data from companies about their interview process. In green are the classification of the recruitment process between labor demand side (companies) and labor supply side (candidates).

Figure II: Interview request acceptance rate as a function of the bid to ask ratio

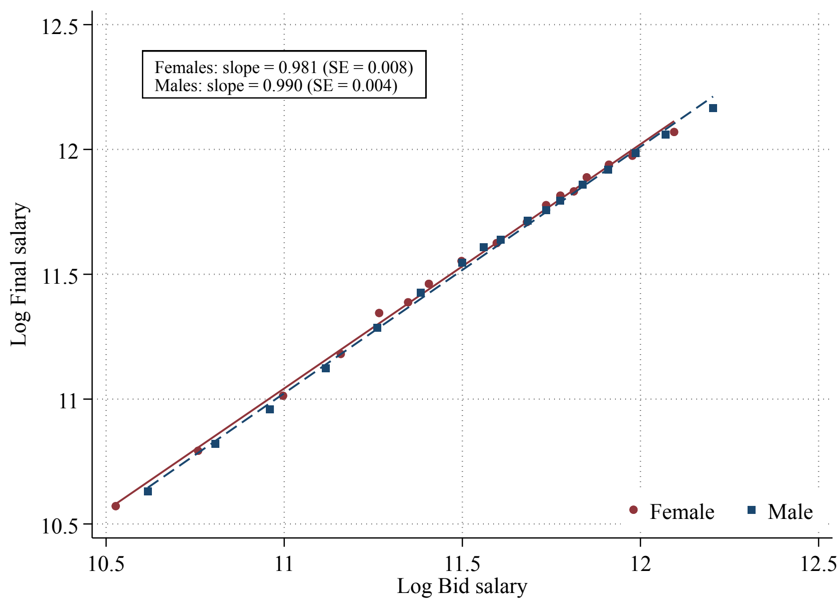


Note: This figure shows how the share of accepted interview requests changes with the ratio of bid to ask salary, separately for male and female candidates. Observations are grouped into bins of $\frac{bid}{ask}$ of length 0.05, except $\frac{bid}{ask}$ =1, which is plotted separately. This figures includes, for each candidate, the first five bids received to ensure that the candidate is active and available for interviews on the platform at the time he or she receives the request.

Figure III: The relationship between ask, bid and final salary



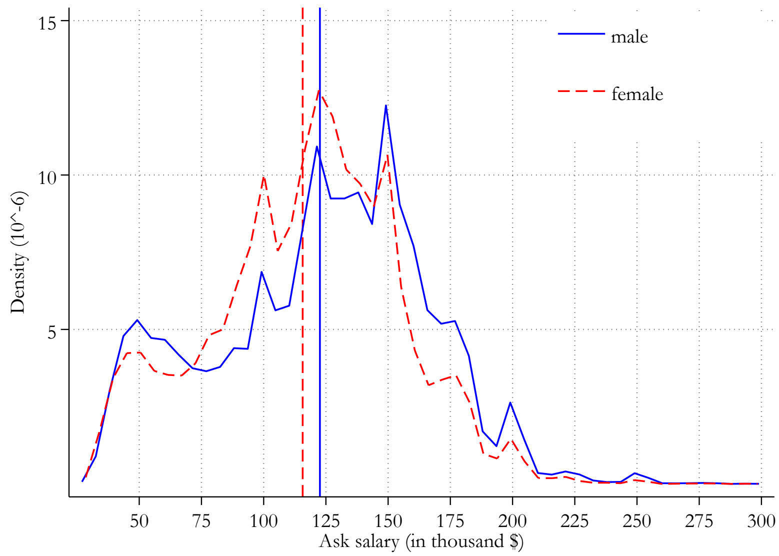
(a) The relationship between log bid and log ask salary



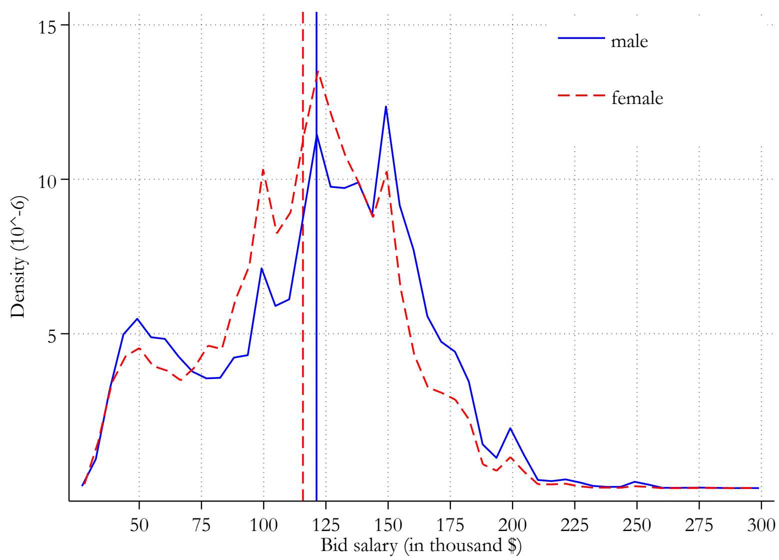
(b) The relationship between log final and log bid salary

Note: This figure shows the close relationship between the log ask and log bid salary in panel (a) and the log bid and log final salary offers in panel (b). It reports these relationships separately for men and women. The difference in the relationships between salaries is not significant by gender. Standard errors are clustered at job and individual level and the binned scatterplots have 16 equal size bins of observations. Overall, 77% of bid salaries are identical to the corresponding ask salary and 90% of bid salaries are within a range of 10k USD from the ask, while 36% of final salaries match the initial bid exactly and 78% of final salaries are within a range 10k USD from the bid. The figure includes the 463,860 observations with an associated bid and the 7,582 observations for which there is a final offer.

Figure IV: Kernel density of ask and bid salaries



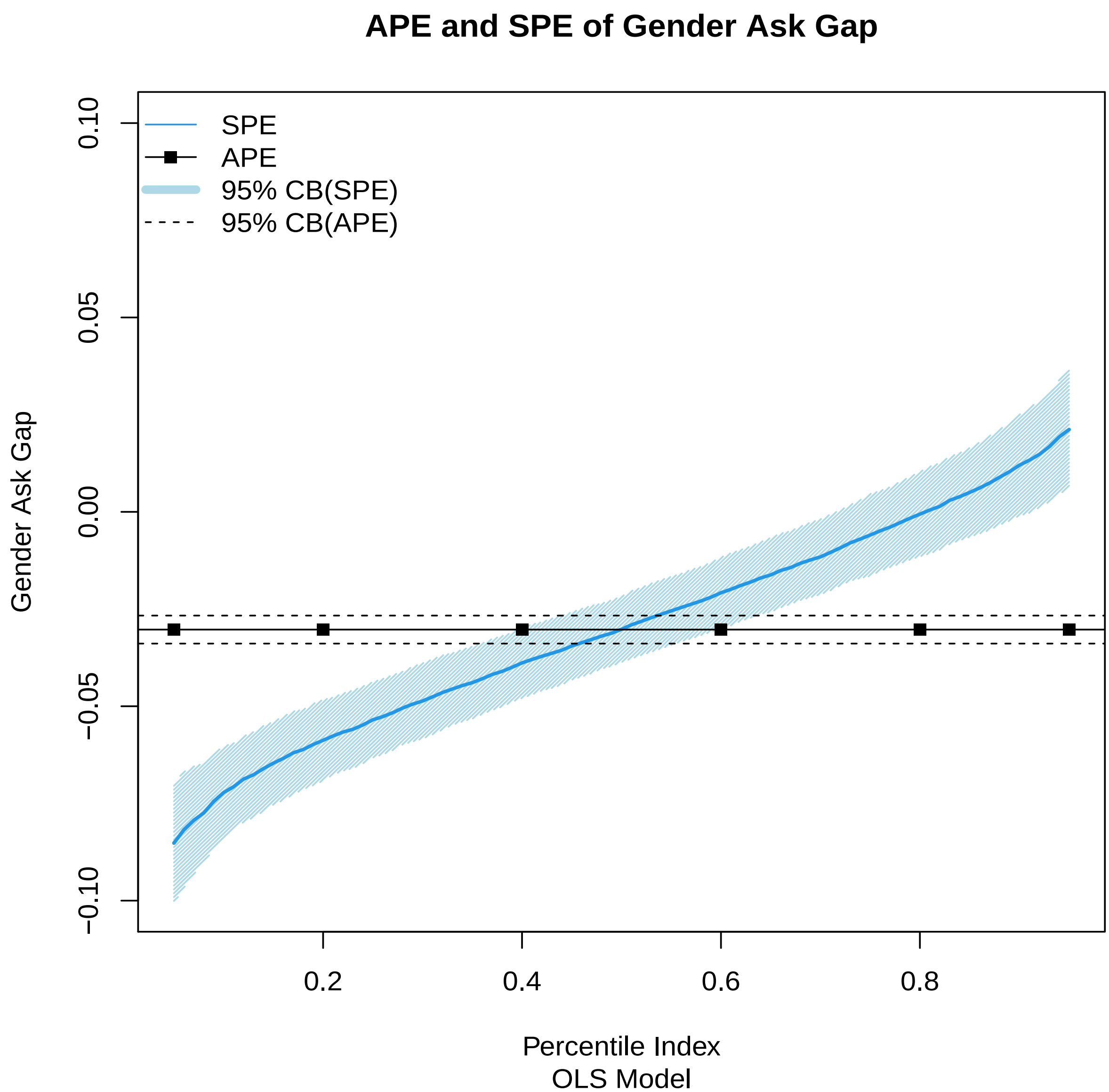
(a) Kernel density of ask salaries



(b) Kernel density of bid salaries

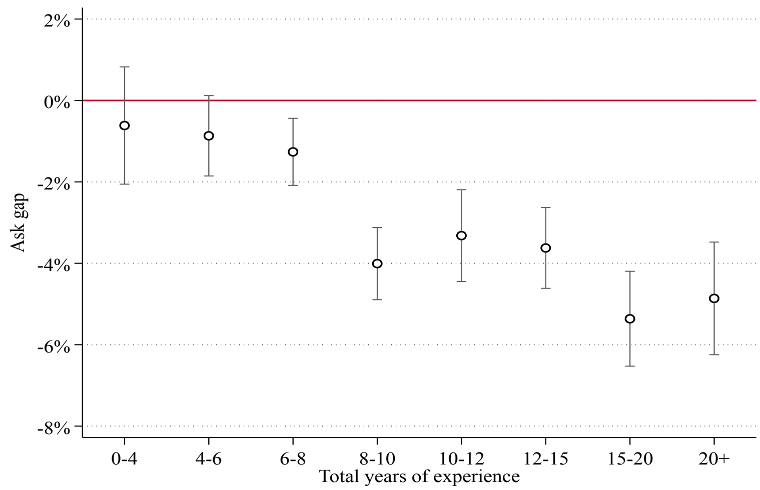
Note: This figure plots kernel density estimates of the distributions of ask (Figure IVa) and bid (Figure IVb) salaries, separately for male (solid blue line) and female (dashed red line). Vertical lines indicate the mean salary respectively for male and female. The kernel density estimates for bid salaries includes all 463,860 bids and the kernel density estimates for ask salaries includes all 113,777 ask salaries, weighted by the number of bids received by the candidate.

Figure V: Sorted Effects of the gender ask gap

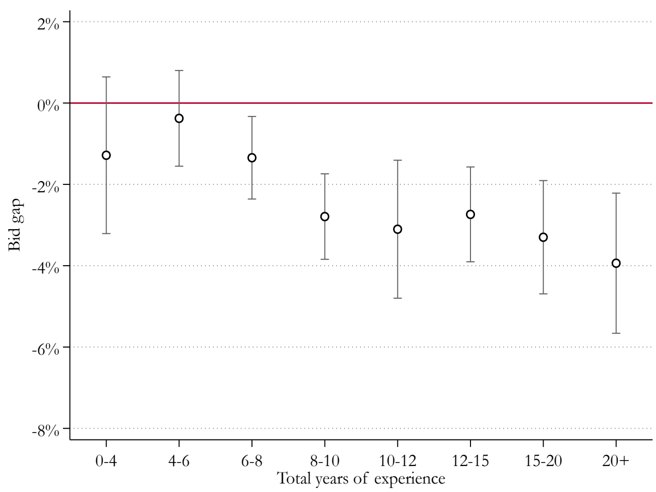


Note: This figure shows the degree of heterogeneity in the ask gap by reporting percentiles of the sorted partial effects (SPE), in addition to the average partial effect (APE), from a regression model where the female dummy is fully interacted with the resume characteristics. The method is described in Chernozhukov, Fernàndez, and Luo (2018) and I used the corresponding spe package on R (Chen et al. (2019)) to implement the sorted method and graph this plot. 95% bootstrap uniform confidence bands (see derivation in paper) are shaded in blue.

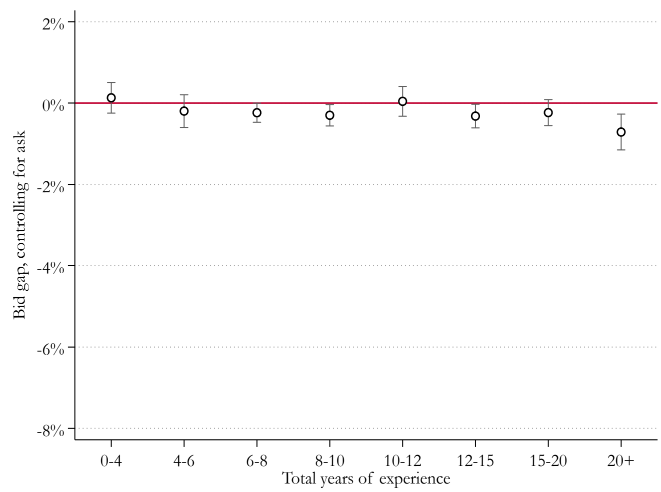
Figure VI: Heterogeneity in the ask and bid gap by experience



(a) Residual Ask gap - resume characteristics



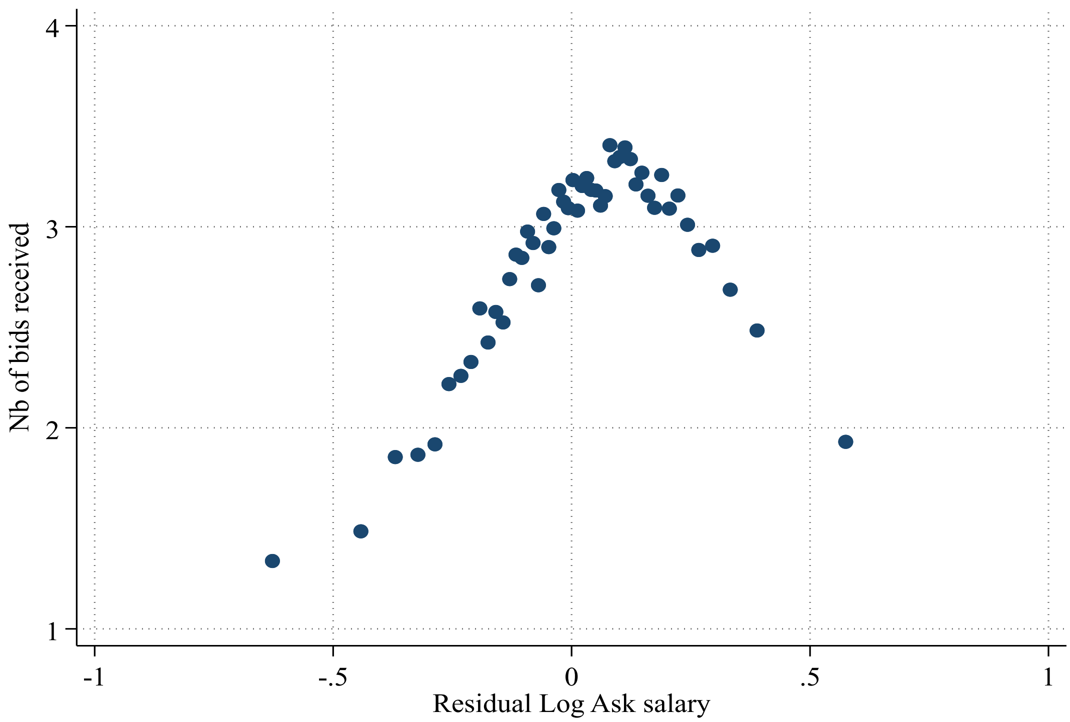
(b) Residual Bid gap - resume characteristics



(c) Residual Bid gap - resume characteristics + ask salary

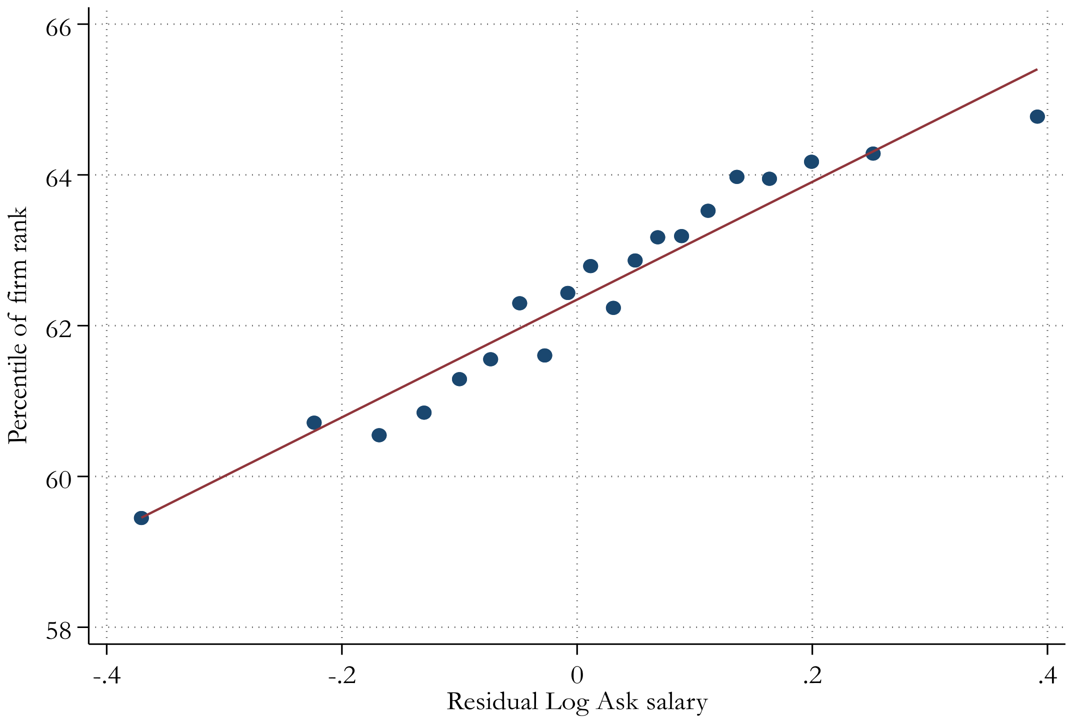
Note: Figure VI shows the heterogeneity in the ask gap by experience as well as the importance of the ask salary in explaining the bid gap, separately by experience. Figure VIa plots the point estimate of the female dummy in Equation 2, where the regression is run separately by total years of experience. Figure VIb plots the point estimate on the female dummy in Equation 5 and Figure VIc plots the point estimate on the female dummy in Equation 6. In all figures, regressions are ran separately for each group of total years of experience.

Figure VII: Binned scatter plot of the number of bids received as a function of the residual log ask salary



Note: This figure shows the relationship between the number of bids received by a candidate during a spell on the platform and the log ask salary of this candidate, residualized on all the resume characteristics of the candidate's profile. The underlying data contains the individual spells of all candidates.

Figure VIII: Binned scatter plot of firm rank as a function of the residual log ask salary

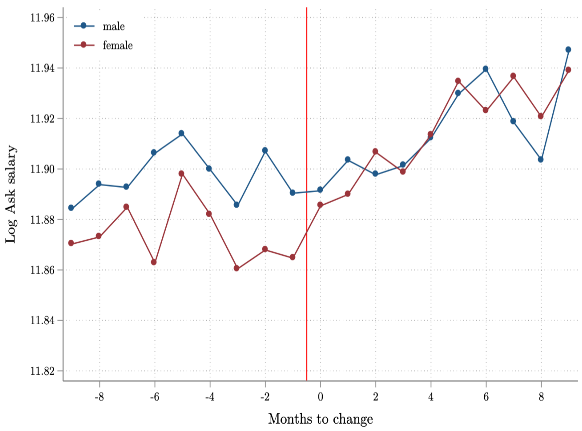


Note: This figure shows the relationship between the percentile of a firms' rank (as in Roussille and Scuderi 2022) and the log ask salary residualized on candidates' resume characteristics for the subsample of firms that can be ranked. Appendix Table C.10 presents the effect of gender on this relationship. Reported standard errors are clustered on candidate and job id level.

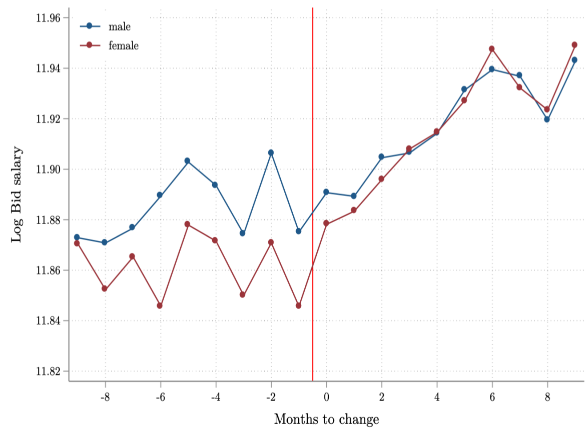
Figure IX: Ask feature change on the platform

Note: This figure shows the effect of the reform on the candidate's ask salary elicitation when they create their profile. In the top figure is the question design before the reform: the answer box is empty. In the bottom figure is the question design after the reform: the answer box is pre-filled with the median bid salary corresponding to the candidate's profile (here a software engineer in San Francisco with similar experience).

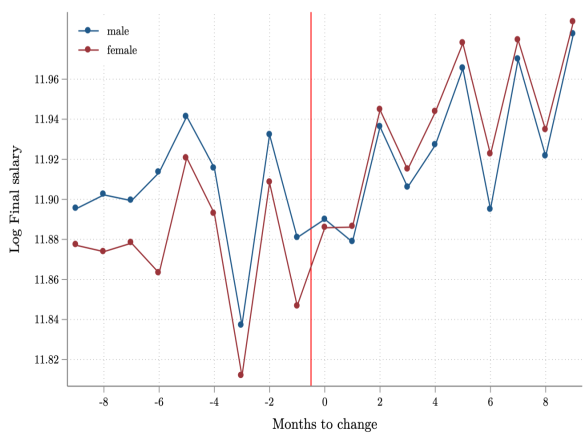
Figure X: Effect of the reform on the gender ask and bid gaps



(a) Log ask salary - all resume controls



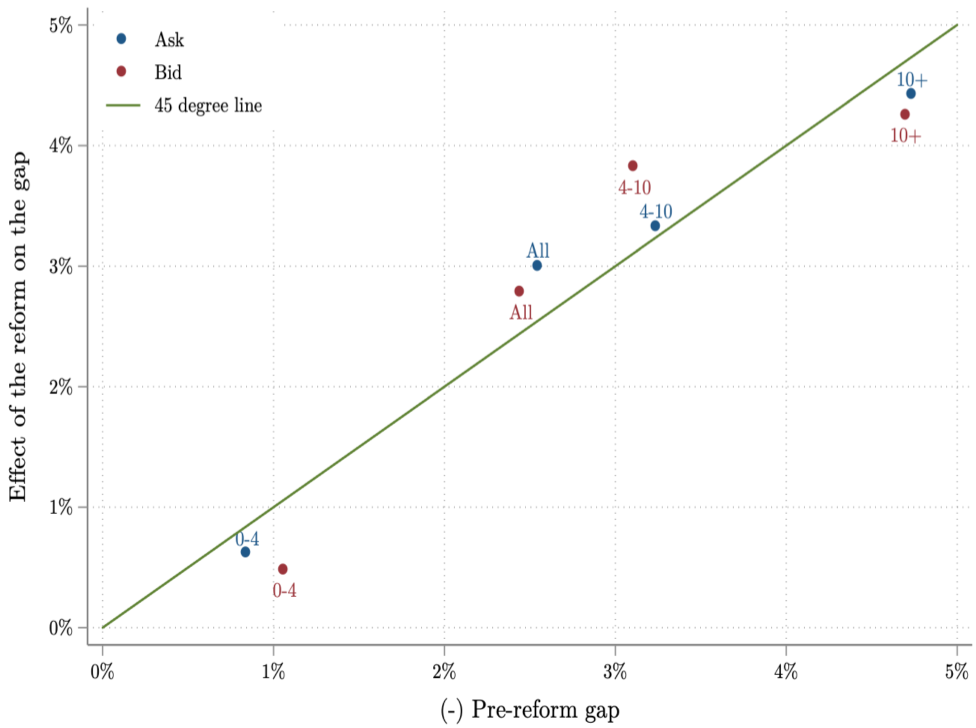
(b) Log bid salary - all resume controls



(c) Log final salary - all resume controls

Note: These figures plot the time series of annual mean salary for men and women, net of all resume characteristics. Each panel is constructed regressing the outcome variable (either log ask salary for Figures Xa, log bid salary for Figure Xb or log final salary for Figure Xc) within every month on a female indicator and the resume controls, requiring that the vertical distance between the two lines equals the regression coefficient on the female indicator and that the weighted average of the lines equals the sample average in that month. The ask salary regressions are bid-weighted (each observation is weighted by the number of bids received).

Figure XI: The effect of the reform on the bid and ask gap as a function of the pre-reform gaps



Note: This figure plots the effect of the reform on the bid and ask gap as a function of the pre-reform gap, separately for three terciles of experience groups. The x-axis is the coefficient on the female dummy in Equation 8, except the observations are weighted by the number of bids received. The y-axis is the coefficient on the female dummy in Equation 9. Regressions are ran separately for each experience group.

Tables

Table I: Descriptive statistics on candidates

Candidate Side					
Variable (mean)	All	Male	Female	Difference	p-value
Number of Candidates	113,777	76,223	19,998	56,225	
Average number of bids received per candidate	4.5	4.6	4.2	0.3	0.000
Probability of accepting an interview request	62.2	62.0	63.2	-1.2	0.000
Education					
Share with a bachelor	97.6	97.3	98.7	-1.4	0.000
Share with a master	41.4	40.3	45.2	-4.9	0.000
Share with a CS degree	55.2	57.2	47.7	9.5	0.000
Share with an IvyPlus degree	9.4	8.7	11.8	-3.1	0.000
Preferences					
Share looking for full time job	96.9	96.7	97.7	-1.1	0.000
Share looking for a job in SF	31.6	30.0	37.5	-7.6	0.000
Share in need of visa sponsorship	13.6	13.0	15.7	-2.7	0.000
Work History					
Years of total experience	11.3	11.7	10.1	1.6	0.000
Share that worked at a FAANG	5.9	5.9	5.8	0.1	0.767
Share leading a team	32.7	33.8	27.6	6.2	0.000
Share employed	73.1	74.0	69.7	4.3	0.000
Number days unemployed	236.2	231.1	253.0	-21.9	0.000
Occupation					
Share of software engineers	61.7	66.6	43.2	23.5	0.000
Share of designers	8.3	6.1	16.6	-10.6	0.000
Share of product managers	8.3	7.5	11.4	-4.0	0.000

Note: This table shows descriptive statistics for candidates. It provides information on the number of candidates, as well as the job search and job finding patterns pooling all companies and all candidates in Column (1) and separating by Gender in Column (2) (Male) and Column (3) (Female). Column (4) shows the difference in means by gender and Column (5) indicates the p-value of the null hypothesis that means are equal. The average number of bids received and probability of accepting is computed on the sample of candidates that receive at least one bid. The table also presents resume characteristics. Column (1) reports means for all candidates, and the remaining columns follow the previously mentioned logic of presenting gender differences in means. Under the category preferences, SF stands for San Francisco. FAANG in the Work History section means Facebook, Amazon, Netflix, Google. The average number of days unemployed is computed conditional on being unemployed. The IvyPlus institutions are Ivy Leagues schools to which I add U. Chicago, Stanford, MIT, and Duke as in Chetty et al. (2017). I also added the schools that are ranked in the top 5 programs in engineering by the annual U.S. News college ranking (e.g. CalTech).

Table II: Descriptive statistics on companies

Company Side						
Variable	**Total**					
Number of firms	6,532					
Number of jobs	39,839					
Number of interview request sent	463,860					
Number of final offers made	7,582					
Average number of bids per job	11.6					
Variable	**Mean**	**SD**	**P10**	**P50**	**P90**	**Nb. Obs.**
Revenue (in Million USD)	708.54	2,651.55	1	15	750	962
Firm age (in years)	9.04	14.94	3	6	14	2,249
Number of benefits	8.49	8.75	0	6	23	2,401
Company Size	**1-10**	**11-50**	**51-200**	**201-500**	**501-1,000**	**1,000+**
(as Share in %)	18%	29%	31%	11%	5%	6%
N = 2368						
Top 3 Locations	**SF**	**NY**	**LA**			
(as Share in %)	42%	18%	7%			
N = 2379						
Top 3 Industries	**Software**	**Finance**	**Analytics**			
(as Share in %)	15%	10%	8%			
N = 2253						
Top 3 Benefits	**Health Ins.**	**Dental Ins.**	**Vision Ins.**			
(as Share in %)	83%	81%	81%			
N = 2401						

Note: This table shows descriptive statistics of the main units of observations on the company side as well as descriptive statistics of firm characteristics for a subsample of companies on Hired.com. For revenue (reported in Million USD), firm age (in years) at the end of our analysis period, and number of benefits that companies list on Hired.com, Columns (1) to (6) report the mean, standard deviation, 10 percent quantile, median, 90 percent quantile and the number of observations respectively for each variable. In the remaining cases the respective share of each category is reported. Company size is measured in number of employees, the 3 most common locations of companies in the US are San Francisco (SF), New York (NY) and Los Angeles (LA), and the three industries in which firms operate most commonly are enterprise software / technical infrastructure, finance & banking, as well as business analytics. Firms can also list benefits on their platform profile which they typically offer to their employees - the three most common being health, dental and vision insurance.

Table III: Gender differences in the ask salary

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.: Log Ask salary							
							Bid-weighted
Female	-0.068***	-0.044***	-0.047***	-0.046***	-0.029***	-0.032***	-0.026***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Experience		X	X	X	X	X	X
City		X	X	X	X	X	X
Occupation		X	X	X	X	X	X
Work preferences			X	X	X	X	X
Education				X	X	X	X
Employment history					X	X	X
Recent company FE						X	
Month $\times$ Year FE	X	X	X	X	X	X	X
Adj R-squared	0.010	0.657	0.669	0.678	0.708	0.706	0.803
Nb. obs	113,777	113,777	113,777	113,777	113,777	113,777	463,860

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents estimates of β_0 from equation 2, progressively adding the controls. Column (1) controls for gender and time fixed effect at the Month $\times$ Year level. Column (2) adds experience, location and job title. The experience controls are a dummied out categorical variable for the number of years of experience in the preferred job title (0-2, 2-4, 4-6, 6-10, 10-15, 15+) and the number of years of total experience (linear and square term) and dummied out categorical variable for the candidates' experience on the platform measured in number of previous spells and length of current spell. The location controls are both the current and desired city of the candidate. The job title control is a (dummied out) categorical variable (e.g. Design) Column (3) adds education controls as described in Table C.1. Column (4) adds work preferences expressed by the candidate such as remote work and sponsorship needs, Column (5), (6) and (7) add controls for employment history, namely a dummy for whether the candidate is currently employed, the number of days of unemployment, the number of people who report to the candidate in his current job (1-5, 5-10 etc), a dummy for whether the candidate has ever worked in one of the FAANG (Facebook, Amazon, Netflix, Google) and a respective dummy whether the candidate has included a link to a personal website or LinkedIn page on the profile. Finally, it adds dummies for the skills that the candidate has (e.g. HTML, Python etc). Column (6) controls for fixed effects of candidates most recent company. For candidates with multiple spells on the platform we select their first ask in Columns (1) to (5). However results are not sensitive to this choice (see Table C.3 showing results are similar if we pick the last ask on the platform). Robust standard errors are used in Column (1) to Column (6). In Column (7) standard errors are clustered at the candidate level.

Table IV: Classification analysis - averages of characteristics of the women with the smallest and largest ask gap

	5% Smallest ask gap	SE	5% Highest ask gap	SE
Total years of experience	7.34	0.41	12.82	0.48
Position experience = 2-4 years	0.39	0.05	0.11	0.02
Position experience = 4-6 years	0.13	0.03	0.20	0.03
Position experience = 6-10 years	0.07	0.02	0.40	0.04
Position experience = 10-15 years	0.01	0.01	0.12	0.03
Position experience = 15+ years	0.01	0.01	0.11	0.03
Employed	0.73	0.04	0.63	0.04
Days unemployed	49.65	11.87	255.89	49.31
Ivy League school	0.20	0.04	0.06	0.02
CS degree	0.55	0.05	0.41	0.04
Java	0.24	0.04	0.19	0.03
HTML	0.16	0.03	0.11	0.02
Python	0.28	0.04	0.11	0.02
JavaScript	0.34	0.04	0.11	0.02
SQL	0.17	0.03	0.28	0.04
data analysis	0.12	0.03	0.09	0.02
pointnet	0.04	0.02	0.01	0.01
C	0.17	0.03	0.03	0.01
Node JS	0.07	0.02	0.05	0.01
CSS	0.15	0.03	0.08	0.02
React	0.18	0.03	0.01	0.01

Note: This table presents partial effects estimated from a linear model with interactions between the female dummy and all resume characteristics. Classification analysis performed using Chernozhukov, Fernàndez, and Luo (2018) procedure. The procedure is implemented on the sample of all candidates' first ask salary in a spell on the platform.

Table V: The role of the ask salary and resume characteristics in bid salary gender differences.

Dep. Var.: Log Bid salary	(1)	(2)	(3)	(4)	(5)
Female	-0.037***	-0.022***	0.002**	-0.002***	-0.002***
	(0.006)	(0.003)	(0.001)	(0.001)	(0.001)
Log Ask salary			0.964***	0.850***	0.849***
			(0.002)	(0.008)	(0.008)
Female × Log Ask salary					0.002
					(0.004)
Constant	11.555***	19.745***	11.593***	13.071***	13.071***
	(0.013)	(0.521)	(0.003)	(0.139)	(0.139)
Candidate's resume characteristics		X		X	X
Month × Year FE	X	X	X	X	X
Adj R-squared	0.028	0.816	0.950	0.954	0.954
Nb. obs	463,860	463,860	463,860	463,860	463,860

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents estimates of β_1 from equation 4 to 7. All regressions include equity as control, and Columns (2), (4) and (5) add the controls in Column (5) of Table III as well as candidates preferences over firm characteristics as described in Table C.1. Column (1) estimates the raw gender bid gap (equation 4); without controlling for equity the bid gap is -0.033. Coefficients in Column (2) correspond to the equation 5. Column (3) only controls for gender and the log ask salary (equation 6). Column (4) presents estimates following equation 7). Column (5) adds an interaction between the female dummy and the log ask salary. Standard errors are two way clustered at the candidate and job id level.

Table VI: The role of the ask salary and resume characteristics in bid salary gender differences for a given job

Dep. Var.: Log Bid salary	(1)	(2)	(3)	(4)	(5)
Female	-0.049***	-0.018***	-0.006***	-0.003***	-0.003***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Log Ask salary			0.806***	0.774***	0.773***
			(0.007)	(0.009)	(0.010)
Female × Log Ask salary					0.003
					(0.004)
Candidate's resume characteristics		X		X	X
Month × Year FE	X	X	X	X	X
Job FE	X	X	X	X	X
Adj R-squared	-0.057	0.281	0.815	0.822	0.822
Nb. obs	454,631	454,631	454,631	454,631	454,631

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents estimates of β_1 from equations 4 to 7, similar to Table V but adding job fixed effects in every column. Standard errors are two way clustered at the candidate and job id level.

Table VII: The role of the ask salary and resume characteristics in final salary gender differences

Dep. Var.: Log Final salary	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.051***	-0.014***	0.023***	0.009**	0.010**	-0.018**	0.002	0.003
	(0.013)	(0.006)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
Log Ask salary			0.955***	0.712***	0.709***		0.617***	0.615***
			(0.007)	(0.026)	(0.028)		(0.023)	(0.024)
Female × Log Ask salary					0.011			0.008
					(0.011)			(0.012)
Constant	11.501***	23.375***	11.601***	14.347***	14.352***	21.736***	14.374***	14.372***
	(0.027)	(1.376)	(0.011)	(0.941)	(0.940)	(1.269)	(0.889)	(0.888)
Candidate's resume characteristics		X		X	X	X	X	X
Month × Year FE	X	X	X	X	X	X	X	X
Firm FE						X	X	X
Adj R-squared	0.034	0.828	0.886	0.903	0.920	0.944	0.920	0.944
Nb. obs	7,582	7,582	7,582	7,582	7,582	7,582	7,582	7,582

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents estimates of β_1 from equations 4 to 7, except the left hand side is $Log(Final_{ib})$ - the salary at which candidate i was hired for the job corresponding to bid b - instead of $Log(Bid_{ib})$. Accordingly, controls are the same as the corresponding columns in Table V. The regression in Col (1) includes equity as an control, without equity the estimated coefficient on female is -0.046. The regressions are ran on the sample of final offers. Columns (6), (7) and (9) add firm fixed effects to Column (2), (4) and (5) respectively. Standard errors are two way clustered at the candidate and job id level level (a few jobs are offered to several candidates and, conversely, a few candidates receive several job offers).

Table VIII: Gender differences in the number of bids received

Dep. Var.: Number of bids received	(1)	(2)	(3)	(4)	(5)
Female	-0.397***	0.229***	0.261***	0.273***	0.342***
	(0.035)	(0.032)	(0.032)	(0.032)	(0.094)
Ask salary			0.930***	1.919***	0.972***
			(0.062)	(0.068)	(0.058)
Ask salary^2				-0.228***	
				(0.014)	
Constant	3.977***	-44.222***	-52.891***	-57.065***	-52.941***
	(0.099)	(4.888)	(4.879)	(4.866)	(4.879)
Poisson AME on Female	-0.402	0.304	0.331	0.362	0.328
Candidate's resume characteristics		X	X	X	X
Month × Year FE	X	X	X	X	X
Adjusted R-squared	0.015	0.241	0.245	0.247	0.245
Nb. obs	164,799	164,799	164,799	164,799	164,799

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table assesses whether there are gender differences in the number of bids received during a candidate's spell on the platform. It is important to note that regressions are at the spell level. Indeed, there are 113,777 candidates and, since some of them are on multiple spells, that sums up to 164,799 spells. Column (1) only controls for gender, Column (2) adds resume characteristics as controls (as in Table V Column (5) but without the equity dummy). Column (3) adds the ask salary in 100,000 USD to Column (2). Column (4) adds the square of the ask salary in 100,000 USD to Column (3). Column (5) adds an interaction between the female dummy and the ask salary to Column (3). Standard errors are clustered at the candidate id level.

Table IX: The absence of gender differences in the probability of receiving a final offer after an interview

	(1)	(2)	(3)	(4)
Dep. Var.: Final offer sent after interview				
Female	0.001	0.001	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Ask salary			-0.000	0.023***
			(0.003)	(0.003)
Ask salary^2			0.001	-0.002***
			(0.001)	(0.001)
Constant	0.051***	-1.349***	-1.370***	-1.567***
	(0.003)	(0.212)	(0.212)	(0.248)
Logit AME on Female	0.001	0.000	0.000	-0.018
Candidate's resume characteristics		X	X	X
Month × Year FE	X	X	X	X
Job FE				X
Adjusted R-squared	0.000	0.008	0.008	-0.146
Nb. obs	261,518	261,518	261,518	261,518

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table assesses whether there are gender differences in the probability of getting a final offer after an interview. Each observation is one bid but the sample is restricted to bids that led to an interview. In other words, bids that were rejected by the candidate, so that there was no interview, are not in the sample. Column (1) to (3) have the same controls as corresponding columns in Table VIII.

Table X: Predicted ask gap using a model fitted on the pre-reform sample

	(1)
Female × After	-0.003
	(0.006)
After	0.002
	(0.003)
Female	-0.080***
	(0.003)
Adj R-squared	0.02
Nb. obs	43368

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table tests the stability over time of the predicted ask gap using a model fitted on pre-reform data. The sample is all San Francisco software engineers in the dataset. The predicted log ask salary (dependent variable) is obtained fitting Equation 2 on the pre-reform sample of SF software engineers, except that instead of Month × Year FE, there are just Month FE (1-12) and a monthly linear time trend. Standard errors are robust.

Table XI: The effect of the reform on the gender ask gap

	(1)	(2)	(3)	(4)	(5)
Dep. Var.: Log Ask salary					
	All	0-4	4-10	10+	Bid-weighted
Female $\times$ After	0.035***	0.016*	0.040***	0.036*	0.030***
	(0.006)	(0.009)	(0.012)	(0.020)	(0.009)
Female	-0.029***	-0.015***	-0.039***	-0.037***	-0.025***
	(0.003)	(0.005)	(0.007)	(0.014)	(0.005)
After	0.007*	0.025***	0.007	-0.011	-0.015**
	(0.004)	(0.007)	(0.008)	(0.010)	(0.006)
Mean Dep. Var.	11.78	11.61	11.84	12.00	11.87
Candidate's resume characteristics	X	X	X	X	X
Adj R-squared	0.517	0.355	0.364	0.285	0.493
Nb. obs	43,368	17,017	19,089	7,262	207,640

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents estimates of β_0, β_1 and β_2 from equation 8 controlling for all candidate's resume characteristics as well as month dummies (1-12) for seasonal adjustments and a linear time trend. It focuses on the effect of the reform on the gender ask by work experience. Column (1) and (5) provide estimates for Equation 8 over all levels of work experiences at the spell and the the candidate $\times$ bid level respectively. Column (2) to (4) provide estimates for Equation 8 separately for three terciles of experience in the candidate's occupation. Observations are at the spell level. Standard errors are clustered at the candidate id level.

Table XII: The effect of the reform on the gender bid and final gap

	Log Bid salary						Log Final salary
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	0-4	4-10	10+	All	All-FE	Final
Female × After	0.028***	0.005	0.038**	0.045*	0.002	0.022	0.019
	(0.011)	(0.014)	(0.018)	(0.026)	(0.007)	(0.009)	(0.035)
Female	-0.025***	-0.011*	-0.031***	-0.047***	-0.004***	-0.018	-0.018
	(0.004)	(0.006)	(0.006)	(0.013)	(0.001)	(0.003)	(0.012)
After	-0.002	0.003	-0.001	-0.009	0.002	0.001	-0.002
	(0.007)	(0.011)	(0.010)	(0.012)	(0.003)	(0.006)	(0.019)
Log Ask salary					0.816***		
					(0.008)		
Mean Dep. Var.	11.86	11.70	11.89	12.01	11.86	11.86	11.86
Candidate's resume characteristics	X	X	X	X	X	X	X
Job FE						X	
Adj R-squared	0.514	0.469	0.379	0.300	0.865	0.252	0.519
Nb. obs	173,765	47,311	99,200	27,254	173,765	167,645	2,074

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents estimates of β_0, β_1 and β_2 from equation 9 as well the corresponding coefficients for the log final salary controlling for all candidate's resume characteristics as well as month dummies (1-12) for seasonal adjustments and a linear time trend. It focuses on the effect of the reform on the gender ask by work experience. Column (1) provides estimates for Equation 9 over all levels of work experiences at the spell and the the candidate × bid level respectively. Column (2) to (4) provide estimates for Equation 9 separately for three terciles of experience in the candidate's occupation. Column (5) adds the log ask salary as a control to Column (1). The sample is all software engineers in San Francisco. Column (6) adds job identifier fixed effects to Column (1). Observations are at the bid level. Column (7) provides estimates analogous to Column (1) but for log final salaries. Standard errors are two-way clustered at the candidate and job id level.

Table XIII: The effect of the reform at the extensive margin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Nb bids	Nb hours	Final offer	Firm rank (bid)	Firm rank (final)	Nb bids	Pred-Nb bids	Pred-Nb bids
Female × After	0.190	0.741	0.006	0.309	0.018	0.037	0.034	0.178
	(0.183)	(4.459)	(0.009)	(0.311)	(0.922)	(0.179)	(0.109)	(0.112)
Female	0.440***	1.115	-0.003	0.335	0.035	0.569***	-0.191***	-0.191***
	(0.112)	(1.796)	(0.005)	(0.251)	(0.812)	(0.110)	(0.066)	(0.069)
After	-0.215*	-4.501*	-0.008	0.290	0.310	-0.252**	0.149***	0.174***
	(0.124)	(2.647)	(0.007)	(0.220)	(0.710)	(0.122)	(0.049)	(0.050)
Ask salary						0.047***		
						(0.003)		
Ask salary^2						-0.000***		
						(0.000)		
Poisson AME on Female × After	0.222	-1.738	0.009					
Mean Dep. Var.	4.79	62.33	0.09	62.5	62.9			
Candidate's resume characteristics	X	X	X	X	X	X		
Adj R-squared	0.227	0.109	0.033	0.242	0.032	0.092	0.002	0.002
Nb. obs	43,368	32,043	43,368	188,463	2,074	43,368	43,368	43,368

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table estimates the effect of the reform at the extensive margin. Column (1) provides estimates for the regression of the number of bids on the female dummy, the after dummy and their interaction, with controls for the candidate's resume characteristics. Column (2) provides estimates for the regression of the log number of hours before a candidate's first bid and Column (3) presents estimates for the regression whether a final offer was provided on the same variables. The sample is all software engineers in San Francisco. Observations are at the spell level. Standard errors are clustered at the candidate id level. Column (4) adds the ask salary and ask salary squared in 100,000 USD to Column (1). The dependent variable in Column (5) is the predicted number of bids received using Column (1) specification on the pre-period. The dependent variable in Column (6) is the predicted number of bids received using Column (4) specification on the pre-period.

A Appendix Model

This section provides a framework that formalizes the insight that the ask salary can be a signal of quality.

Wolinsky (1983) shows that, in a context of imperfect information about product quality, there exists a separating fulfilled expectations equilibrium: each price signals a unique quality level and if all agents expect that a product at price p has quality q, then this expectation is in turn fulfilled by agents' behavior.

In this section, I adapt Wolinsky (1983)'s model to the labor market and show that there exists an *at least*-fulfilled expectations separating equilibrium: each ask salary signals a unique candidate quality and if all firms expect that a candidate with ask salary a has quality q, then this expectation is in turn either fulfilled or surpassed by the candidate.

The intuition for the equilibrium in this model can be summarized as follows. At a given ask salary, firms expect a certain quality of candidate. A candidate that asks for a given salary may turn out to be of lower quality, but information revealed during the interview will enable some potential firms to discover it. Therefore, in deciding whether to ask for a higher salary than what the firm expects given her quality, the candidate weighs the decrease in her chances of being hired against the gain in salary that results if she gets an offer. If the chances of detection are large enough to outweigh the potential salary gains, it is best for the candidate to signal her true quality with her ask salary.

In this model, women have downward biased beliefs about the salary they can ask for that stems from inaccurate information about the equilibrium. There is no mechanism in the model for firms to learn about these biases because interviews go equally well for men and women. This feature of the model comes from the way the signal is designed: the candidate's quality signal revealed during the interview can be interpreted as "red flag", that is whether the candidate falls below her expected quality. However, in equilibrium, neither men nor women end up triggering this flag. When women are debiased they ask for more but interviews still lead to a hire because they remain strictly above the firm's minimal quality threshold.

The key testable prediction that comes out of this model is a link between the number of bids and the ask salary ala Figure VIII. In the model, firm types are characterized by the range of ask salaries they are willing to interview. I use my data to measure the interview strategies of large employers and show that demand for ask salaries is upward sloping over the same range as found in Figure VIII and downward sloping afterwards, thereby corroborating the ask salary as a signal of quality mechanism.

A.1 Sequence of actions

There are two types of agents, the firms, denoted by $j \in J$, and the candidates, denoted by $i \in I$. First, Nature draws a discrete quality $q \in Q$ and gender $g \in (m, f)$ - male or female - for candidate i. Second, candidate i sets his or her ask salary. Third, the firm decides whether to ask a candidate for an interview. During the interview, the firm pays a small cost c and receives a signal about the quality of the candidate. Based on this signal, the firm decides whether or not to hire this candidate.

A.2 Firms

Each firm seeks to hire one candidate. Firms can observe candidates' ask salary a_i but not their quality q_i so they have to form expectations about the latter. $q^e(a_i)$ are common point expectations that assign a single quality level, $q \in Q$, to each candidate ask salary a_i, where $q^e(.)$ is increasing in a_i. $q^e(a_i)$ is labelled common point expectations because all firms believe that quality $q^e(a_i)$ is offered by candidates that ask for a_i. Firms differ in the returns they derive from the expected quality of candidate i, $q^e(a_i)$. In particular, a firm of type k ($k = A, ..., Z$) derives a benefit of $m_k(q^e)$, where $m_k(.)$ is strictly increasing in q^e, but the slope differs by type k. One can think of m_k as a match-productivity parameter: the highest quality types have a higher return if the job includes complex tasks. A firm decides whether to hire the candidate only after interviewing him/her. In the course of the interview, firm j gets some information on q_i. This information is represented by a signal d_i^j which depends on q_i and random factors. Without loss of generality, assume that the conditional distribution of d_i^j is identical for all j. Let $D(t, q)$ denote the distribution function of d_i^j conditional on q_i.

$$D(t, q) = \mathbb{P}(d_i^j < t | q_i = q)$$

It is assumed that there is a positive probability that d_i^j will enable firm j to establish with certainty that candidate i's quality is not greater than q_i. Formally:

- For every q there exists a t such that $D(t, q) = 0$.
- Let $t(q) = sup[t | D(t, q) = 0]$, then $q_1 < q_2 \longrightarrow t(q_1) < t(q_2)$.

Similar to Wolinsky (1983), the ask salary of the candidate is modelled as a price: To interview the candidate, the firm commits to paying them their ask salary if the candidate is hired. In other words, we do not consider that the firm can bid or make a final offer below or above the ask salary of the candidate.[33]

Before hiring, a firm can interview as many candidates as it likes. Any interview, whether or not it ends in a hire, involves a fixed cost of interviewing c. If firm j goes to n candidates and ends up hiring candidate i at their ask salary a_i, its expected profit will be $m_k(q^e(a_i)) - a_i - nc$. The firm's goal is to maximize this expression.

A.3 Candidates

Candidates choose their ask salary so as to maximize their expected benefit, that is the product of their ask salary and the probability that they get hired.

Candidates of type q want to maximize the salary offers they receive for a given q^e. We assume Bertrand competition between firms. Therefore, candidates set their ask salary so that the expected benefit to a firm of type $k_i^* = \arg\max \left[k' \in K | m_{k'}^g(q^e(a_i)\right]$ is zero and $g \in (m, f)$. This means that for each expected quality level, candidates target their ideal firm, that is the one that has the most returns, and therefore the highest willingness to pay for, that expected quality level. In equilibrium, as described in Section A.5, this condition provides a mapping between a candidate's quality and its ask salary.

The cost of interviewing to the firm, c, is common knowledge. Firms assume $m_k(.)$ is common knowledge as well. However, I model the fact that women ask for less on average as resulting from women receiving downward-biased information about $m_k(.)$. This assumption is in line with the information channel that is put forward to explain the effect of the reform in section 7. For tractability we model this downward-bias by assuming that women observe m_k^f instead of the true m_k, where $m_k^f(q^e) = m_k(q^e - 1)$, while men received information about the true match-productivity parameter, that is $m_k^m(q^e) = m_k(q^e)$.

For a given type k, it is assumed that firms request an interview from all the (yet unsampled) candidates whose ask salary is in the range that maximises the firm's expected profit. Candidates agree to interview with one of the available firms they received an interview request from, at

[33] This simplification allows the model to focus on its main narrative, which is that the ask salary is a signal of quality. It also does not depart radically from the empirical evidence: 78% of the bids are made exactly at the ask salary of the candidate.

random.[34]

After an interview, the probability that the candidate is hired is 1 if their ask salary signals at least their true quality q_i and $1 - D[t(q_i'), q_i]$ if their true quality q_i is less than the quality their ask salary suggests q_i'.

The goal of candidate i with quality q is to maximize her expected benefit. If the candidate signals her true quality q_i the expected benefit is $a_i(q_i)$. If the candidate signals a quality q_i' above the true quality q_i, the expected benefit is $a_i(q_i') \times (1 - D[t(q_i'), q_i])$. Here we assume the candidate can interview with at most one firm: if he/she does not get hired, the other firms will know this candidate lied about their quality and therefore will not want to interview him/her.

A.4 Separating equilibrium conditions

Definition: A separating equilibrium is characterized by common point expectations $q^e(a)$, candidates I with ask salary choices $\overline{a_i}$, $\overline{A} = (\overline{a_i})$, and firm strategies $\overline{S} = [(\overline{s_j})]$, such that the conditions (C-1)-(C-4) hold:

(C-1) Candidate expected-benefit maximization: $\overline{a_i} \in \overline{A}$ maximizes i's expected benefit, for all $i \in I$

(C-2) Firm's profit maximization: Given $\overline{A}$ and $q^e(.)$, strategy $\overline{S}$ maximizes j's expected benefit, for all $j \in J$

(C-3) Credibility of firm's strategy: Let i be the first candidate sampled by j. The response prescribed by $\overline{s_j}$ to the event that $d_i^j < t[q^e(a_i)]$ remains optimal after the event has occurred.

(C-4) At least-fulfilled expectations: $q_i \geq q^e(\overline{a_i})$ for all $i \in I$.

Condition (C-2) requires $\overline{S}$ to be optimal but not necessarily in the face of the unexpected deviations. Condition (C-3) extends it by requiring optimality of $\overline{S}$ in the event that firm j encounters unexpectedly a deviating candidate and gets a signal $d_i^j < t[q^e(a_i)]$. The rationale for this requirement is that the equilibrium choices of candidates will depend on how firms "threaten" to respond to deviations, and for these "threats" to convince the candidates they have to be credible in the sense of condition (C-3). Condition (C-4) is an equilibrium concept rather than a condition of individual rationality.

[34] For Bertrand competition between firms to hold we need to assume that, for each candidate, there are at least two firms willing to hire them based on their ask salary.

A.5 Solving for the separating equilibrium

The point expectations $q^e(.)$ imply a simple form of firm strategy. Every firm will go to a candidate whose ask salary maximises its profit, it will hire that candidate unless it realizes that this candidate's quality is lower than expected; in that event it will go to another candidate. On the candidate side, the key is to find the sufficient condition under which (C-4) holds, that is candidates signal at least their true quality. Signalling a quality q' higher than the true quality q has two opposing effects. On the one hand, the candidate's expected benefit increases because of the salary increase in the event the candidate is hired $(a(q') > a(q))$. On the other hand, the candidate's expected benefit decreases because of the increased risk of being detected as lower quality and therefore not being hired. In particular, the probability of getting hired when signalling one's true quality is 1, while it is only $(1 - D[t(q'), q]$ when signalling q'. Putting these together, the expected benefit from declaring q' is $a(q')(1 - D[t(q'), q])$ while that of declaring q is $a(q)$. The sufficient condition under which the candidate does not signal a quality above his true quality is that for all $q, q' > q \in Q$:

$$
\begin{aligned}
&a(q')(1 - D[t(q'), q]) < a(q) \Leftrightarrow \\
&\frac{a(q')}{a(q)} < \frac{1}{(1 - D[t(q'), q])}
\end{aligned} \tag{1}
$$

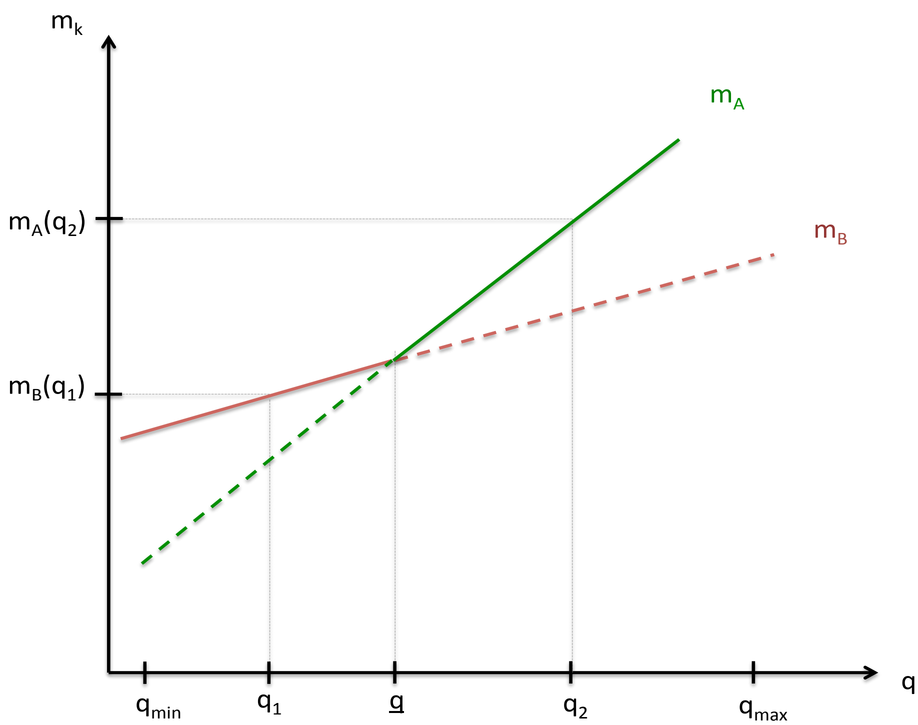
This condition means that for any $q' > q$, the relative increase in the salary in the event of a hire has to be lower than the relative decline in the probability be hired. Note that there is no point in signalling a quality q'' lower than the true quality q since that reduces the ask salary but does not change the likelihood of hire.

If condition 1 is satisfied, then given firm's behaviour, a candidate i expects to be hired only by firms who happen to choose them for their first interview. This is because the candidate believes that all other candidates ask for salaries matching the quality expected from them and therefore always get hired after an interview. In other words, $n = 1$.

We now have all the elements to construct the exact mapping between a candidate's quality and her optimal ask salary. From section A.3 and the fact that in equilibrium $q^e = q$, we know that candidates set their ask salary so that the expected benefit of the firm of type $k_i^* = \arg\max\left[k' \in K | m_{k'}^g(q(a_i)\right]$ is zero, with $g \in (m, f)$. An example with just two firms and male candidates, provides intuition for this condition. Assume firm A and B respectively have match-productivity parameter $m_A(q)$ and $m_B(q)$, where $m_a'(q) > m_b'(q)$ and the two functions cross at $\underline{q}$

as in Figure A.1. Assume $q \in (q_{min}, \underline{q})$, then the optimal strategy is to target Firm B with an ask salary that sets firm B's profit to zero, that is $a = m_B(q) - c$. Conversely, if $q \in (\underline{q}, q_{max})$, Firm A will be targeted and the ask salary will be $a = m_A(q) - c$. From the firm's perspective, this provides a one-to-one mapping from firm types to ask salary ranges: firms of type A will interview candidates whose ask belongs to $(q_{min} - c, \underline{q} - c)$ and firms of type B will interview candidates whose ask belongs to $(\underline{q} - c, q_{max} - c)$.

Figure A.1: Candidate's target firm choice - two firm example



Note: This figure represents, in equilibrium, the relationship between the quality of candidates and the match productivity parameters of two firms with different types, A and B. Firm A's $m_A(q)$ is in green and Firm B's $m_B(q)$ is in red. The solid line is the upper envelope of the two firm's matching parameters and indicates the candidate's target firm at each quality level. Firm A is targeted for quality in the $(q_{min}, \underline{q})$ range and firm B is targeted for for quality in the $(\underline{q}, q_{max})$ range.

Given their information about m_k, the optimal ask salary for women is $a^*_{if} = m^f_k(q_i) - c = m_k(q_i - 1) - c$ and for men is $a^*_{im} = m^m_k(q_i) - c = m_k(q_i) - c$. Given these ask salaries, firms predict that women are of quality $q_i - 1$ and offer them $m_k(q_i - 1) - c$, while they predict men are of quality q_i and offer them $m_k(q_i) - c$. The key to this being an equilibrium outcome is that while women are indeed of higher quality for a given ask salary, firms do not know or learn about it in this setting.

This feature of the model comes from the fact that, in equilibrium, the probability of detecting that men are below the expected quality is the same as for women (zero) and therefore the recruitment process per se does not reveal gender-specific information about quality. Conversely, women with quality q_i would benefit from asking for more but, given their beliefs, asking for a^*_{if} is the expected benefit maximising choice.

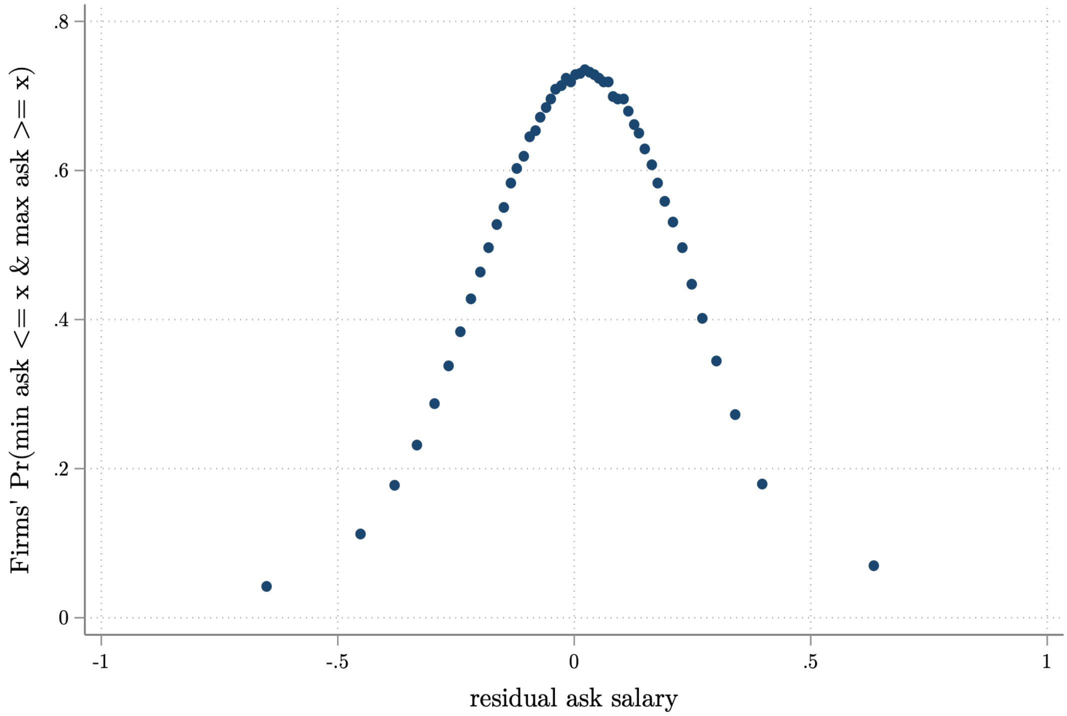
A.6 Reform impact for women

Assume women were provided with information on $m_k(.)$, so that their beliefs now match those of men.

Impact on salary: Before the information provision, women asked for $m_k(q-1)-c$, firms predict that women are of quality $q_i - 1$ and offer them $m_k(q_i-1)-c$. After the information provision, women of quality q shift their beliefs to $m_k'^f = m_k(q^e)$ and, in equilibrium, they ask for $m_k(q)-c$, companies think they are of quality q and offer women $m_k(q)-c > m_k(q-1)-c$. In sum, women ask for more - the same as men - and correspondingly get more.

Impact on the number of interview requests received: For a given type k, firms request an interview from all the (yet unsampled) candidates asking for a salary that is in the range that maximises the firm's expected profit. As described earlier, this provides a one-to-one mapping between firm types and a profit-maximising ask salary range in which each firm type interviews. Therefore, the model predicts that the impact of the change in women's ask on the number of interview request received depends on two elements: (1) the empirical distribution of the number of firms willing to interview at a given ask salary and (2) where in this distribution women lie before and after the information provision. We can define as "min ask" the lowest ask salary at which a given firm interviews and "max ask" as the highest one. Figure A.2 then describes, for a given ask salary, the share of firms on the platform for which this ask salary fits into their interview range, $[\text{min ask}, \text{max ask}]$. Given the mapping between the profit-maximising ask salary range and firm types, this figure provides the empirical distribution of firm types. From this bell-shape relationship we can conclude that a sufficient condition for the information provision to have had a positive impact on the number of interview requests received by women is that enough of them had an initial ask salary that was in the increasing range of the figure.

Figure A.2: Empirical distribution of firm types



Note: The model predicts that, in equilibrium, a firm's type is defined by the range of ask salaries at which it interviews, [min ask, max ask]. This figure therefore provides, for each ask salary, the share of firms for which this salary falls in their type's interview range. The sample is restricted to firms that send more than 20 interview requests.

B Appendix Figures

Figure B.1: Mandatory features of a candidate profile, at the time of the study

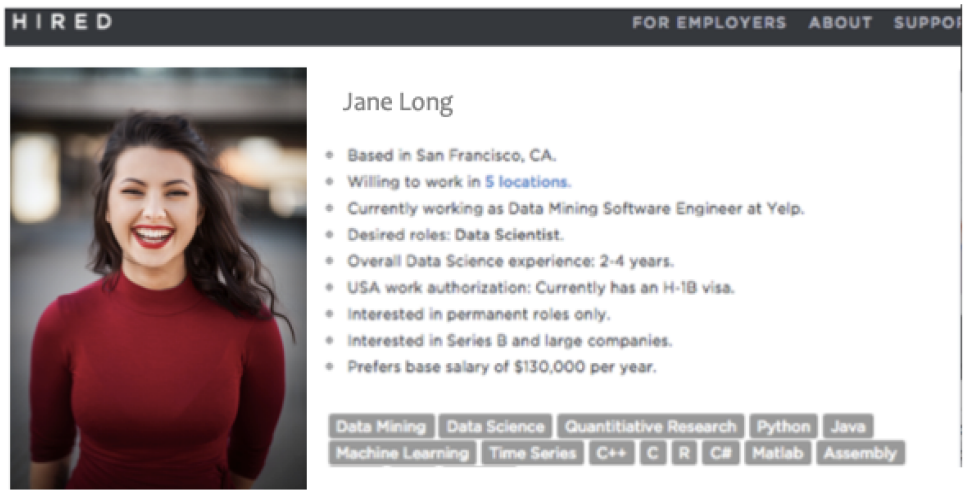


Figure B.2: Typical interview request message sent by a company to a candidate, at the time of the study

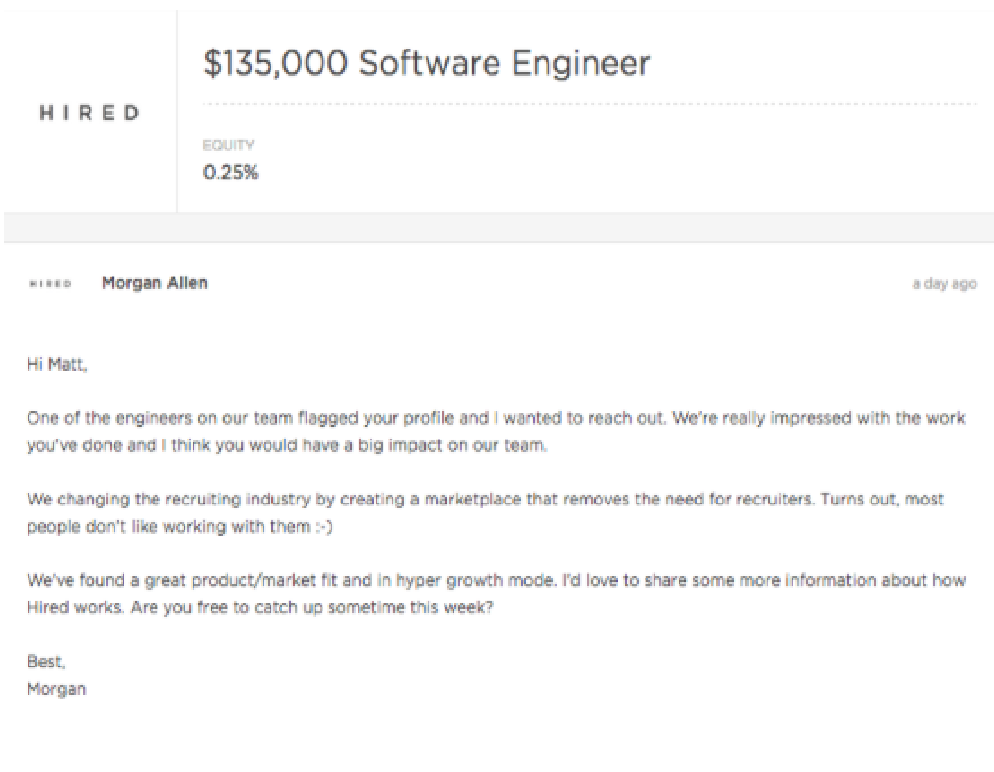
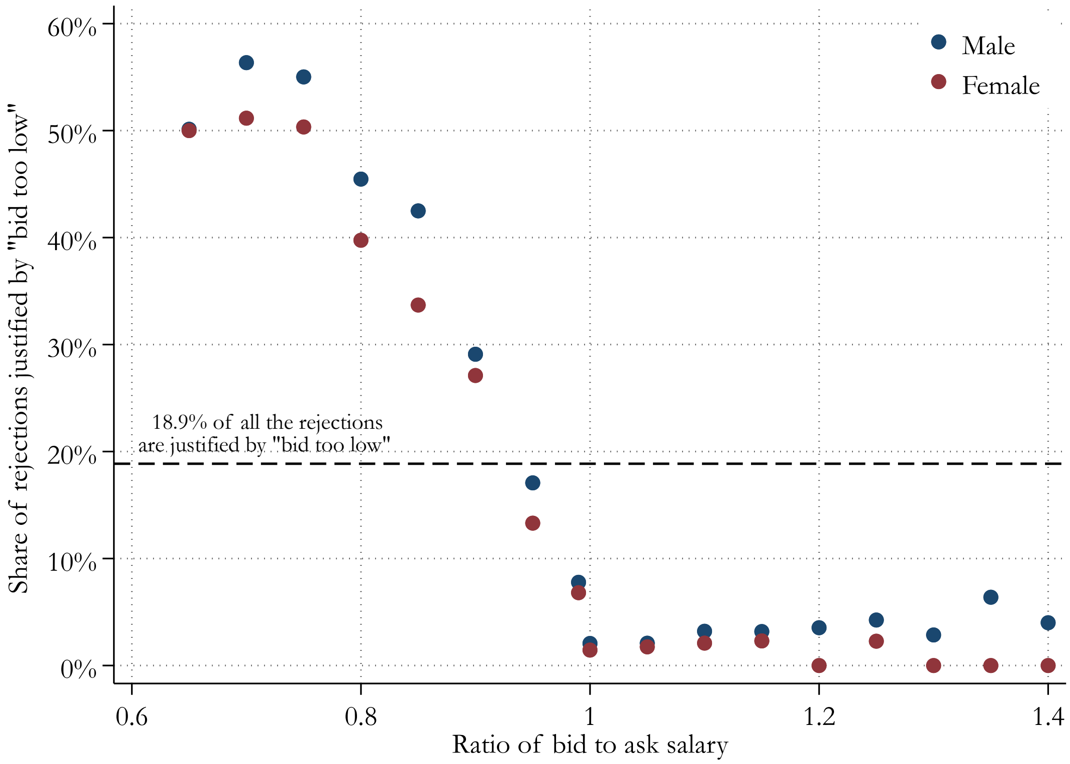
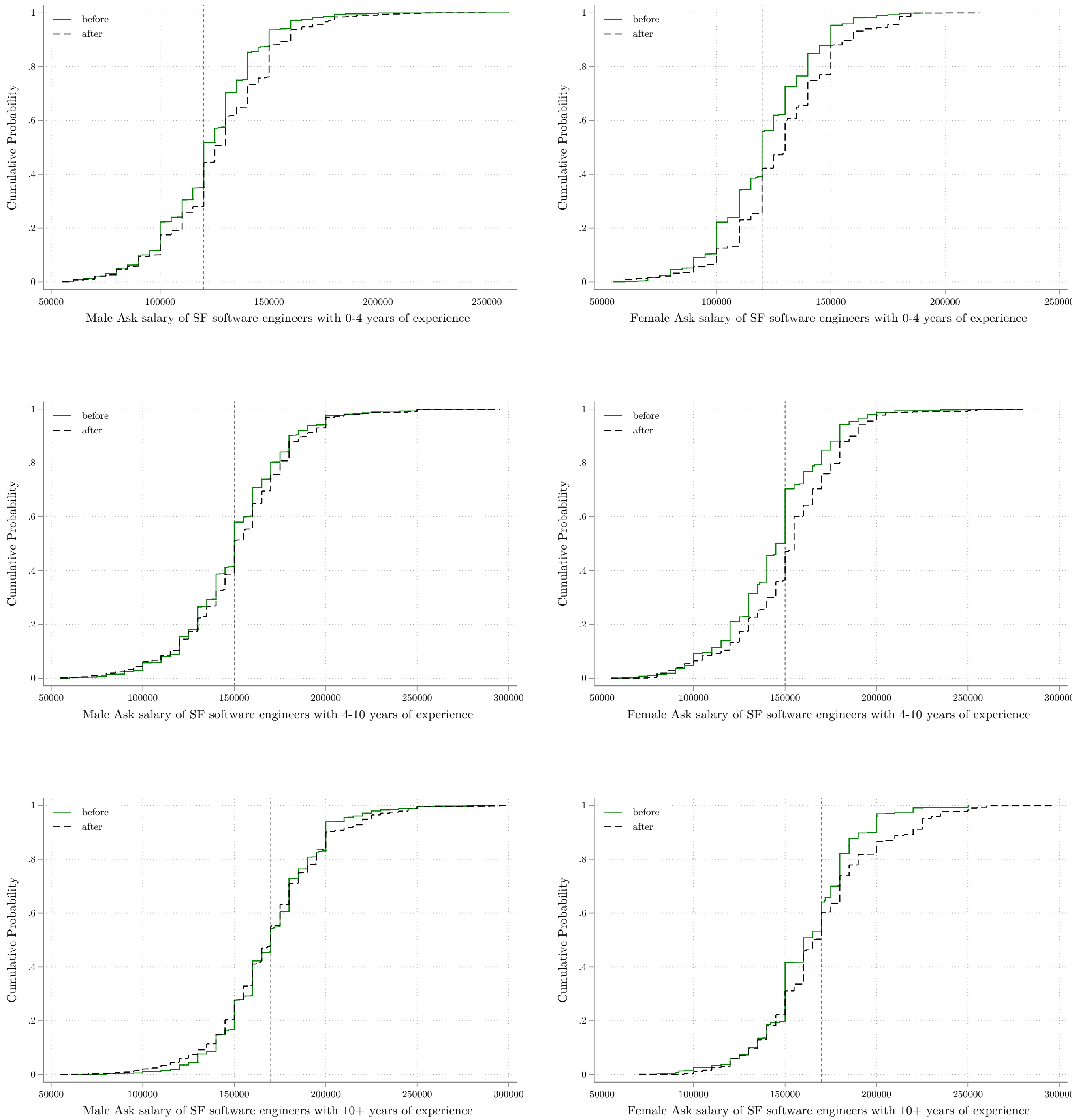


Figure B.3: Interview request rejection reason as a function of the bid to ask ratio



Note: This figure shows that the share of rejected interview requests because the bid was too low decreases with the ratio of bid to ask salary, separately for male and female candidates. When a candidate receives a bid, he can decide to reject it, that is he can refuse to interview with the company. They can choose from justifications such as "company culture", "company size", or "insufficient compensation". The latter is the justification we label as "bid too low".

Figure B.4: Cumulative distribution function of candidates' ask salaries before and after the reform



Note: This figure plots the cumulative density of ask salaries, separately for different levels of experience (top to bottom), for male (left) and female (right), before (full green line) and after (dashed black line) the reform. Given that salary suggestion are made at the experience level, all candidates of a given experience have seen the same suggestion. The exact median that was shown was not logged but the grey line approximates it using the past 12 months of bids for the corresponding experience. The before period is limited to 12 months for better comparability of ask salaries.

C Appendix Tables

Table C.1: Fields of a candidate profile and other variables used as controls

Resume characteristics	Type of variable	Controls in the regression
Fields from the candidate profile		
What type of position do you currently have? (job title)	categorical variables - drop down menu - single entry	• Software Engineering • Engineering management • Design • Data Analytics • Developer Operations • Quality Assurance • Information Technology • Project management • Product management
Total Position experience (in years)	categorical variables - drop down menu - single entry	• 0-2 years • 2-4 years • 4-6 years • 6-10 years • 10-15 years • 15+ years
Skills : Rank your top 5 languages & skills	categorical variables - drop down menu - multiple (up to 5 entries, at least 1)	Choice from many categories, the most cited (>10% of the time) are: • javascript • python • sql • c • nodejs • ruby • css • react. All CS skills that are cited by more than 0.05% of the sample are included as dummies in the regression.[35]
Where do you live?	categorical variables - drop down menu - single entry	• San Francisco • Los Angeles • San Diego • Seattle • Denver • Austin • Houston • Chicago • Boston • Washington D.C. • New York
Where do you want to work?	categorical variables - drop down menu - single entry	• San Francisco • Los Angeles • San Diego • Seattle • Denver • Austin • Houston • Chicago • Boston • Washington D.C. • New York
Are you interested in working remotely?	categorical variables - drop down menu - single entry	• Yes • No • Remote Only
What type of employment are you seeking?	categorical variables - drop down menu - single entry	• Full Time Only • Prefers Full Time • Full Time Only • Both equally • Prefers Contract • Contract Only
Preferred company size: I'd like to work at a company that has __ employees	categorical variable - drop down menu - multiple entries	Dummies on selected size: • 1-15 • 16-50 • 51-200 • 201-500 • 500+
Preferred industry: My ideal company would be in these industries:	categorical variable - drop down menu - multiple entries	Top ten most chosen industries: • bank, corporate finance, & investing • analytics & business information • e-commerce • health care technology & nursing • hardware, internet of things, & electronics • information systems • education • digital payments • social networking • digital communication
Preferred career path:	categorical variable - drop down menu - multiple entries	Dummies on selected path: • contributional role • manager
Preferred career goal:	categorical variable - drop down menu - multiple entries	Dummies on selected goal: • leadership • great culture • mentorship • new technologies • socially conscious • large projects
Preferred skill to use on job:	categorical variable - drop down menu - multiple entries	Dummies on selected skill: top 5 most selected skills: Python, Java, JavaScript, Product Management, React. The top 30 skills cover 80% of all listed skills and are included as dummies in the regression.

[35] The full set of included dummies is: html, java, python, javascript, ios, pointnet, android, sql, c, ruby, dataanalysis, php, nodejs, css, react, go, r, saas, linux, agile, angular, swift, hadoop, scala

Where are you in your job search?	categorical variables - drop down menu - single entry	• not looking for new opportunities / just browsing • open to exploring new opportunities • actively looking for new opportunities • currently interviewing • have offers
Will you now or in the future require sponsorship for employment visa status (e.g. H-1B Visa)?	categorical variables - drop down menu - single entry	• Sponsorship Required • Not Required
Work experience	Manual entry of the history of firms that the candidate worked at and the roles they had there	Here I built a dummy = 1 if the candidate has ever worked at a "elite" tech company (FAANG - Facebook, Amazon, Netflix, Google) before as well as identify the most recent company the candidate has/is working at.
Job titles	Manual entry of the job title held at each firm the candidate worked at	I created a categorical variable for the highest position held in a firm ("junior", "senior", "manager", "lead","head", "director") as well as whether the candidate ever was a founder at a company.
Education	Manual entry of educational institution, degree and year	Here I built 5 variables: categorical for highest degree achieved (high school, Associate, Bachelor, Master, MBA, PhD), the average global ranking as reported on Webometrics of all schools the candidate attended grouped into six categories (1-20, 21-100, 101-500, 501-1,000, 1,001-5,000, and 5,000+) , dummy for whether the degree is in CS (computer science), the graduation year, and dummy for whether the candidate ever attended an IvyLeague+ school (as defined in Chetty et al. (2017)) - to which I added schools that are ranked in the top 5 programs in engineering by the annual U.S. News college ranking (UC Berkeley, California Institute of Technology, Carnegie Mellon University and Georgia Institute of Technology).
Number of reports (i.e. the number of people who report to you)	categorical variables - drop down menu - single entry	• 1-5 • 6-10 • 11-20 • 20+
External Websites	links to external LinkedIn page or personal website	Here I built two dummies: one dummy when a candidate has included at LinkedIn profile and one dummy when the candidate links to a personal website

Other control variables

Equity	-	Dummy whether equity of company was included in bid to candidate
Total experience	-	Number of years of experience, enters linearly and squared in the regression
Employed	Dummy variable	• Yes • No
Number of days searching for work	-	number of days searching for work (linearly enters the regression)
Number of past spells on the platform	Categorical variable	• 1 • 2 • 3 • 4+
Month × Year	-	FE for the Month × Year
Length of spell on the platform	categorical variable	Number of days the profile is live on the platform (15 - 22 - 29 - 36 - 43) - only enters regressions at the extensive margin

Table C.2: Relationship between gender and expressed preferences over firm characteristics

	No Preference	**Preferred Company Size**					**Preferred Industry**				**Preferred Career Goal**			
Dep. Var.:		1-15	16-50	51-200	201-500	500+	Hardware, IoT	Finance	Education	Health-Tech	New Technologies	Leadership	Mentorship	Socially Conscious
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Female	0.013***	-0.004	-0.031***	0.004	0.009***	0.021***	-0.011***	-0.007***	0.005***	0.007***	-0.013***	-0.003	0.006**	0.023***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)
Male mean	0.252	0.469	0.432	0.453	0.433	0.351	0.033	0.041	0.026	0.028	0.249	0.189	0.090	0.088
Candidate's resume characteristics	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Month × Year FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
Adj R-squared	0.211	0.405	0.363	0.383	0.366	0.289	0.125	0.148	0.132	0.122	0.348	0.277	0.159	0.149
Nb. obs	113,777	113,777	113,777	113,777	113,777	113,777	113,777	113,777	113,777	113,777	113,777	113,777	113,777	113,777

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents estimates of a subset of candidates' expressed preferences over company size in Columns (2) to (6), industry in Columns (7) to (10), and career goals in Columns (11) to (14) on gender. Column (1) presents estimates for whether any preference was listed on Hired.com. Standard errors are robust.

Table C.3: The last ask salary as a function of gender and resume characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.: Log Ask salary							
							Bid-weighted
Female	-0.071***	-0.044***	-0.047***	-0.045***	-0.028***	-0.030***	-0.026***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Experience		X	X	X	X	X	X
City		X	X	X	X	X	X
Occupation		X	X	X	X	X	X
Work preferences			X	X	X	X	X
Education				X	X	X	X
Employment history					X	X	X
Recent company FE						X	
Month × Year FE	X	X	X	X	X	X	X
Adj R-squared	0.009	0.657	0.670	0.680	0.712	0.629	0.803
Nb. obs	113,777	113,777	113,777	113,777	113,777	113,777	463,860

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents estimates of β_0 from equation 2, progressively adding the controls. Column (1) controls for gender and time fixed effect at the Month × Year level. Column (2) adds experience, location and job title. The experience controls are a dummied out categorical variable for the number of years of experience in the preferred job title (0-2, 2-4, 4-6, 6-10, 10-15, 15+) and the number of years of total experience (linear and square term) and dummied out categorical variable for the candidates' experience on the platform measured in number of previous spells and length of current spell. The location controls are both the current and desired city of the candidate. The job title control is a (dummied out) categorical variable (e.g. Design) Column (3) adds education controls as described in Table C.1. Column (4) adds work preferences expressed by the candidate such as remote work and sponsorship needs, Column (5), (6) and (7) add controls for employment history, namely a dummy for whether the candidate is currently employed, the number of days of unemployment, the number of people who report to the candidate in his current job (1-5, 5-10 etc), a dummy for whether the candidate has ever worked in one of the FAANG (Facebook, Amazon, Netflix, Google) and a respective dummy whether the candidate has included a link to a personal website or LinkedIn page on the profile. Finally, it adds dummies for the skills that the candidate has (e.g. HTML, Python etc). Column (6) controls for fixed effects of candidates most recent company. Robust standard errors for Column (1) to Column (6). In Column (7) standard errors are clustered at the candidate level.

Table C.4: Ask Gap Corrected for Unobservables following Altonji, Elder, and Taber (2005)

Treatment Variable	**Baseline Effect**			**Controlled Effect**			**Identified Set**		**R max**
	Coefficient	(Std. Error)	[R-sqrd]	Coefficient	(Std. Error)	[R-sqrd]	for $\beta = 0$,	$\tilde{\delta} = 1$	
Female	-0.062	(0.003)	[0.003]	-0.029	(0.002)	[0.708]	[-0.029	-0.013]	1

Note: This table presents the results of the selection exercise on observable and unobservable variables as proposed by Altonji, Elder, and Taber (2005). $\beta = 0$ represents the null of the non-existence of the gender ask gap. As the identified set for the coefficient on the ask gap does not include 0, the null can be rejected.

Table C.5: Estimates for controls other than gender in Equations 2 and 7 and for final offers

	Log Ask salary		Log Bid salary			Log Final salary		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.068***	-0.029***	-0.037***	-0.022***	-0.002***	-0.051***	-0.014**	0.010**
	(0.003)	(0.002)	(0.006)	(0.003)	(0.001)	(0.013)	(0.006)	(0.004)
Employed		0.069***		0.043***	0.003***		0.032***	0.007*
		(0.002)		(0.002)	(0.001)		(0.005)	(0.004)
Log Ask salary					0.849***			0.709***
					(0.008)			(0.028)
Female × Log Ask salary					0.001			0.011
					(0.004)			(0.011)
Years of experience in the desired occupation								
2-4		0.106***		0.093***	0.011***		0.104***	0.018***
		(0.002)		(0.003)	(0.001)		(0.008)	(0.006)
4-6		0.199***		0.174***	0.020***		0.188***	0.038***
		(0.003)		(0.004)	(0.002)		(0.009)	(0.007)
6-10		0.299***		0.245***	0.027***		0.253***	0.045***
		(0.003)		(0.004)	(0.002)		(0.010)	(0.009)
10-15		0.345***		0.275***	0.030***		0.282***	0.044***
		(0.004)		(0.005)	(0.003)		(0.014)	(0.012)
15+		0.378***		0.291***	0.030***		0.294***	0.043***
		(0.005)		(0.006)	(0.003)		(0.017)	(0.015)
Education								
Bachelor		0.053***		0.026**	0.004*		0.014	-0.005
		(0.011)		(0.013)	(0.002)		(0.038)	(0.016)
Master		0.086***		0.040***	0.006**		0.037	0.003
		(0.011)		(0.013)	(0.002)		(0.038)	(0.016)
PhD		0.151***		0.081***	0.011***		0.076*	0.019
		(0.012)		(0.013)	(0.003)		(0.040)	(0.019)
University Ranking								
21-100		0.002		-0.001	0.001		-0.004	-0.003
		(0.003)		(0.004)	(0.001)		(0.009)	(0.007)
101-500		-0.021***		-0.019***	0.000		-0.014	-0.004
		(0.003)		(0.004)	(0.001)		(0.010)	(0.007)
501-1,000		-0.038***		-0.027***	-0.000		-0.012	-0.014*
		(0.004)		(0.005)	(0.001)		(0.011)	(0.007)
1,001-5,000		-0.047***		-0.029***	-0.001		-0.016*	-0.000
		(0.003)		(0.004)	(0.001)		(0.010)	(0.006)
5,000+		-0.058***		-0.037***	-0.003***		-0.027***	-0.008
		(0.003)		(0.004)	(0.001)		(0.010)	(0.007)
Constant	11.617***	19.715***	11.555***	19.740***	13.072***	11.501***	23.368***	14.360***
	(0.007)	(0.372)	(0.013)	(0.521)	(0.139)	(0.027)	(1.377)	(0.942)
Candidate's resume characteristics		X		X	X		X	X
Month × Year FE	X	X	X	X	X	X	X	X
Adj R-squared	0.010	0.708	0.028	0.816	0.954	0.034	0.828	0.920
Nb. obs	113,777	113,777	463,860	463,860	463,860	7,582	7,582	7,582

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table provides estimates for controls other than the Female dummy from equation 2 in Column (1) and (2), from 7 in Column (3), (4) and (5), and for the final salary as dependent variable in Column (6), (7) and (8). Column (2) has the same controls as Column (6) in Table III, Column (5) has the same controls as Column (5) in Table V and Column (8) has the same controls as Column (7) in Table VII. The dropped categories for Years of experience is 0-2, for education it is High School and for university ranking it is 1-20. Robust standard errors are used for Column (1) and (2) and for Column (3) - (8) standard errors are clustered at the job and candidate level.

Table C.6: The ask salary (in USD) as a function of gender and resume characteristics

	(1)	(2)
Dep. Var.: Log Ask salary		
Female	-8581***	-3823***
	(329)	(231)
Employed		7194***
		(239)
Years of experience in the desired occupation		
2-4		8514***
		(280)
4-6		17649***
		(322)
6-10		29372***
		(362)
10-15		35156***
		(489)
15+		40522***
		(606)
Education		
Bachelor		3749***
		(1086)
Master		7472***
		(1094)
PhD		15029***
		(1198)
Constant	117295***	975481***
	(757)	(46356)
Candidate's resume characteristics		X
Month $\times$ Year FE	X	X
Adj R-squared	0.010	0.606
Nb. obs	113,777	113,777

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table provides estimates for coefficients in equation 2, where the left hand side variable is Ask_i instead of $Log(Ask_i)$. Column (1) controls for gender and time fixed effect at the Month $\times$ Year level. Column (2) has the same controls as Column (5) in Table III. Robust standard errors are used.

Table C.7: Explaining the spread between offer and ask salaries

	Log(Bid)-Log(Ask)	Log(Final)-Log(Ask)
	(1)	(2)
Female	0.001*	0.018***
	(0.001)	(0.005)
Employed	-0.005***	-0.003
	(0.001)	(0.004)
Years of experience in the desired occupation		
2-4	-0.003***	-0.016***
	(0.001)	(0.006)
4-6	-0.007***	-0.022***
	(0.001)	(0.006)
6-10	-0.012***	-0.039***
	(0.001)	(0.007)
10-15	-0.013***	-0.052***
	(0.002)	(0.009)
15+	-0.015***	-0.058***
	(0.002)	(0.013)
Education		
Bachelor	-0.000	-0.013
	(0.002)	(0.013)
Master	-0.000	-0.011
	(0.002)	(0.013)
PhD	-0.001	-0.005
	(0.003)	(0.016)
Constant	0.275*	-0.917
	(0.142)	(0.934)
Candidate's resume characteristics	X	X
Month × Year FE	X	X
Adj R-squared	0.021	0.047
Nb. obs	463,860	7,582

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table explores the role of controls other than gender in explaining the spread between the bid and the ask of a candidate (Column (1)) and the final offer and the ask of a candidate (Column (2)). For all columns, controls are the same as in Table V. The first column contains all bids in the sample, the second column contains all final offers in the sample. Standard errors are two way clustered at the candidate and job id level.

Table C.8: Gender differences in characteristics of firms bidding candidates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Var.:	**Company Size**					**Revenue**	**Number of**	**Top 3 Industries**		
	0-50	50-200	200-500	500-1500	1500+	(Million USD)	**Benefits**	Software	Finance	Analytics
Female	0.013***	0.008**	0.003	-0.014***	-0.010**	-64.281	-0.080	-0.011***	0.003	-0.007***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(61.409)	(0.110)	(0.004)	(0.003)	(0.002)
Log Ask salary	-0.080***	-0.039***	0.054***	0.058***	0.007	-586.848***	3.018***	0.011	0.003	-0.006
	(0.009)	(0.011)	(0.011)	(0.010)	(0.009)	(147.921)	(0.280)	(0.010)	(0.009)	(0.010)
Share of category	0.22	0.26	0.17	0.15	0.20			0.20	0.10	0.08
Candidate's resume characteristics	X	X	X	X	X	X	X	X	X	X
Month $\times$ Year FE	X	X	X	X	X	X	X	X	X	X
Adj R-squared	0.044	0.022	0.014	0.018	0.077	0.079	0.057	0.039	0.024	0.027
Nb. obs	277,061	277,061	277,061	277,061	277,061	149,783	278,343	274,810	274,810	274,810

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents the relationship between a selection of firm characteristics that are reported on the company's webpage on Hired.com and gender for the subsample of bids for which the respective firm characteristics can be identified. In Columns (1) to (5) we define dummies whether the bidding firm size is within the respective range of employees. Similarly, Columns (8) to (10) report estimates regressing for dummies whether the firm operates in one of the three most frequent industries in the sample. The dependant variable in Column (6) is revenue reported in Million USD and in Column (7) the number of benefits a company lists on Hired.com is regressed on the set of covariates which are in all Columns identical to Column (5) in Table III + candidates' preferences over firm characteristics. Standard errors are clustered at candidate and job id level.

Table C.9: Probability of accepting an interview requests by gender and firm characteristics

	(1)	(2)	(3)	(4)
Dep. Var.: Prob. of accepting				
Female	0.055	0.053	0.050	0.048
	(0.081)	(0.077)	(0.082)	(0.078)
Company Size				
Female × 50-200	0.002	0.003	0.003	0.003
	(0.008)	(0.008)	(0.008)	(0.008)
Female × 200-500	0.040***	0.039***	0.039***	0.038***
	(0.010)	(0.009)	(0.009)	(0.009)
Female × 500-1,500	0.039***	0.040***	0.040***	0.041***
	(0.012)	(0.012)	(0.011)	(0.011)
Female × 1,500+	0.048***	0.051***	0.047***	0.050***
	(0.015)	(0.015)	(0.015)	(0.015)
Revenue (Million USD)				
Female × 25-500	0.005	0.005	0.005	0.005
	(0.010)	(0.010)	(0.010)	(0.010)
Female × 500-5,000	0.007	0.006	0.008	0.007
	(0.016)	(0.016)	(0.016)	(0.016)
Female × 5,000+	0.005	0.005	0.007	0.007
	(0.015)	(0.015)	(0.015)	(0.015)
Female × Number of benefits	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Top 3 Industries:				
Female × Software	-0.068	-0.067	-0.069	-0.068
	(0.081)	(0.077)	(0.081)	(0.078)
Female × Finance	-0.083	-0.079	-0.084	-0.080
	(0.081)	(0.077)	(0.081)	(0.078)
Female × Analytics	-0.092	-0.089	-0.092	-0.089
	(0.081)	(0.077)	(0.082)	(0.078)
Mean acceptance prob.	0.56	0.56	0.56	0.56
Firm preferences controls		X		X
Ask, bid and equity controls			X	X
Candidate's resume characteristics	X	X	X	X
Month × Year FE	X	X	X	X
Adj R-squared	0.062	0.069	0.072	0.078
Nb. obs	274,050	274,050	274,050	274,050

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents the effect of gender interacted with firm characteristics on the probability of accepting an interview requests. Controls in Column (1) are identical to controls in Column (5) of Table III, while Column (2) adds candidates' preferences over firms. Column (3) adds the ratio of bid to ask salary as well as the equity dummy as control and Column (4) includes firm preferences. The omitted category for company size is 0-50 employees, 0-25 million for the revenue category and agriculture is omitted for industries. Standard errors are clustered at candidate and job id level.

Table C.10: The ask salary as signal of quality: relationship between firm rank and the residual log ask

	Firm rank (bid)			Firm rank (final)		
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-1.795***	-0.040	0.164	-1.241	0.827	1.220
	(0.406)	(0.283)	(0.278)	(1.181)	(1.167)	(1.170)
Log Ask salary			8.781***			13.081***
			(0.755)			(2.424)
Constant	60.840***	227.974***	166.998***	60.013***	321.969	157.829
	(1.337)	(36.269)	(35.370)	(2.993)	(253.126)	(253.622)
Mean rank percentile	62.5	62.5	62.5	64.3	64.3	64.3
Resume Characteristics		X	X		X	X
Month × Year FE	X	X	X	X	X	X
Adj R-squared	0.004	0.042	0.045	0.005	0.088	0.095
Nb. obs	259,749	259,749	259,749	3,454	3,454	3,454

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table assesses whether there are gender differences in the ranking of firms sending interview requests to candidates. It reports estimates for the subsample of data for which firms can be ranked (see Roussille and Scuderi 2022). The ranking estimates are normalized as percentiles from 0 to 100 where 100 is the best possible ranking. Column (1) controls for gender and Month × Year FE. Column (2) adds resume characteristics as controls and Column (3) includes candidates' log ask salary. Column (4) to (6) progressively add controls in the same way as Column (1) to (3) but on the subset of observations that include a final offer. Standard errors are clustered at candidate and job id level.

Table C.11: The role of the ask salary and resume characteristics in bid salary gender differences for a given firm

Dep. Var.: Log Bid salary	(1)	(2)	(3)	(4)	(5)
Female	-0.076***	-0.022***	-0.007***	-0.003***	-0.003***
	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
Log Ask salary			0.859***	0.809***	0.808***
			(0.009)	(0.008)	(0.008)
Female × Log Ask salary					0.004*
					(0.002)
Candidate's resume characteristics		X		X	X
Month × Year FE	X	X	X	X	X
Firm FE	X	X	X	X	X
Adj R-squared	0.028	0.472	0.869	0.874	0.874
Nb. obs	463,860	463,860	463,860	463,860	463,860

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This tables adds firm FE to the estimates of β_1 from equation 4 to 7. All regressions include equity as control, and further controls are added progressively. Column (1) controls for gender (equation 4); without controlling for equity the bid gap is -0.033. Column (2) has the same controls as Column (6) from Table II (equation 5). Column (3) only controls for gender and the log ask salary (equation 6). Column (4) adds the controls from Column (2) to Column (3) (equation 7). Column (5) has the same controls as in Column (4), adding an interaction between the female dummy and the log ask salary. Standard errors are clustered at the company id level.

Table C.12: The role of the ask salary and resume characteristics in bid salary gender differences - sample restriction: only keep bids for jobs that lead to a hire on the platform

	(1)	(2)	(3)	(4)	(5)
Dep. Var.: Log Bid salary					
Female	-0.038***	-0.023***	0.002**	-0.002***	-0.002***
	(0.008)	(0.003)	(0.001)	(0.001)	(0.001)
Log Ask salary			0.961***	0.843***	0.842***
			(0.003)	(0.010)	(0.011)
Female × Log Ask salary					0.002
					(0.005)
Constant	11.580***	19.659***	11.598***	13.158***	13.159***
	(0.019)	(0.589)	(0.004)	(0.204)	(0.205)
Candidate's resume characteristics		X		X	X
Month × Year FE	X	X	X	X	X
Adj R-squared	0.027	0.809	0.949	0.953	0.953
Nb. obs	201,589	201,589	201,589	201,589	201,589

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This tables presents estimates of the gender bid gap on the subset of bids for jobs that lead to a hire on the platform. For all columns, controls are the same as in Table V. The only difference is the sample since here we only keep bids for jobs that lead to a hire on the platform. Standard errors are two way clustered at the candidate and job id level.

Table C.13: The role of the ask salary and resume characteristics in bid salary gender differences - sample restriction: only keep bids that are different from the candidate's ask

Dep. Var.: Log Bid salary	(1)	(2)	(3)	(4)	(5)
Female	-0.042***	-0.016***	0.006**	-0.003	-0.003
	(0.008)	(0.003)	(0.003)	(0.002)	(0.002)
Log Ask salary			0.850***	0.540***	0.538***
			(0.007)	(0.016)	(0.017)
Female × Log Ask salary					0.005
					(0.011)
Constant	11.487***	20.209***	11.543***	15.674***	15.679***
	(0.017)	(0.781)	(0.007)	(0.518)	(0.518)
Candidate's resume characteristics		X		X	X
Month × Year FE	X	X	X	X	X
Adj R-squared	0.055	0.773	0.807	0.850	0.850
Nb. obs	105,144	105,144	105,144	105,144	105,144

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This tables presents estimates of the gender bid gap on the subset of bids that are different from the candidate's ask salary. For all columns, controls are the same as in Table V. The only difference is the sample: here we only keep bids that are different from the candidate's ask. Standard errors are two way clustered at the candidate and job id level.

Table C.14: The role of the ask salary and resume characteristics in final salary gender differences - sample restriction: only keep final offers that are different from the candidate's ask

Dep. Var.: Log Final salary	(1)	(2)	(3)	(4)	(5)
Female	-0.044***	-0.011	0.029***	0.009	0.010*
	(0.015)	(0.007)	(0.006)	(0.005)	(0.006)
Log Ask salary			0.929***	0.622***	0.619***
			(0.010)	(0.030)	(0.032)
Female × Log Ask salary					0.012
					(0.016)
Constant	11.605***	23.896***	11.603***	15.471***	15.473***
	(0.030)	(1.695)	(0.014)	(1.324)	(1.325)
Candidate's resume characteristics		X		X	X
Month × Year FE	X	X	X	X	X
Adj R-squared	0.013	0.809	0.856	0.889	0.889
Nb. obs	5,273	5,273	5,273	5,273	5,273

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This tables presents estimates of the gender final offer gap on the subset of final offers that are different from the candidate's ask salary. The controls are the same as the corresponding columns in Table VII. The only difference is the sample: here we only keep final offers that are different from the candidate's ask. Standard errors are two way clustered at the candidate and job id level.

Table C.15: The within-candidate effect of a change of ask salary on the bid salary

	(1)	(2)	(3)	(4)	(5)	(6)
Log Ask salary	0.483^{***}	0.484^{***}	0.537^{***}	0.554^{***}	0.398^{***}	0.383^{***}
	(0.034)	(0.041)	(0.039)	(0.044)	(0.056)	(0.066)
Female × Log Ask salary		-0.059		-0.100		-0.012
		(0.094)		(0.112)		(0.151)
Adj R-squared	-0.003	-0.002	0.038	0.039	-0.074	-0.072
RMSE	0.086	0.086	0.083	0.083	0.090	0.089
Nb. obs	39930	39930	26113	26113	13817	13817

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table shows the effect of a within-candidate, within-spell change in the ask salary on the bid salary. This model is ran on the sub-sample of candidates who update their ask salary during their spell. There are individual spell fixed effects, that is a different dummy for each candidate *times* spell. Standard errors are two-way clustered at the candidate and job id level. There are no other controls since resume characteristics do not vary within a candidate × spell cell.

Table C.16: The racial ask, bid and final salary gap

	Log Ask salary		Log Bid salary					Log Final salary				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Female	-0.111***	-0.025***	-0.087***	-0.019***	0.000	-0.001	-0.000	-0.082***	-0.007	0.017**	0.016**	0.017**
	(0.005)	(0.003)	(0.010)	(0.005)	(0.001)	(0.001)	(0.001)	(0.019)	(0.012)	(0.007)	(0.008)	(0.008)
African American	-0.077***	-0.012*	-0.032	-0.004	0.000	-0.001	-0.001	-0.012	-0.027	-0.025	-0.026	-0.044*
	(0.010)	(0.007)	(0.021)	(0.009)	(0.002)	(0.002)	(0.002)	(0.040)	(0.020)	(0.027)	(0.019)	(0.024)
Asian	0.038***	0.010***	0.099***	0.000	0.008***	0.001	0.002	0.066***	-0.001	0.018***	0.001	-0.001
	(0.004)	(0.003)	(0.008)	(0.005)	(0.001)	(0.001)	(0.001)	(0.017)	(0.011)	(0.007)	(0.007)	(0.007)
Hispanic	-0.033***	-0.014***	0.026*	-0.002	0.004**	0.001	0.001	0.035	-0.016	-0.013	-0.021**	-0.020*
	(0.008)	(0.005)	(0.014)	(0.007)	(0.002)	(0.001)	(0.001)	(0.030)	(0.016)	(0.011)	(0.010)	(0.011)
Log Ask salary					0.952***	0.870***	0.870***			0.899***	0.670***	0.711***
					(0.003)	(0.008)	(0.008)			(0.022)	(0.050)	(0.033)
Female × Log Ask salary							0.010**					-0.000
							(0.005)					(0.024)
African American × Log Ask salary							0.003					-0.237*
							(0.010)					(0.136)
Asian × Log Ask salary							-0.009					-0.059
							(0.007)					(0.039)
Hispanic × Log Ask salary							0.006					-0.012
							(0.010)					(0.055)
Constant	11.703***	20.145***	11.633***	19.073***	11.643***	12.558***	12.589***	11.557***	24.326***	11.610***	15.871***	15.397***
	(0.019)	(0.700)	(0.026)	(0.963)	(0.009)	(0.198)	(0.199)	(0.069)	(2.673)	(0.030)	(2.008)	(1.841)
Candidate's resume characteristics		X		X		X	X		X		X	X
Month × Year FE	X	X	X	X	X	X	X	X	X	X	X	X
Adj R-squared	0.037	0.622	0.069	0.731	0.935	0.939	0.939	0.063	0.754	0.856	0.880	0.883
Nb. obs	31,241	31,241	105,851	105,851	105,851	105,851	105,851	1,846	1,846	1,846	1,846	1,846

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table assesses racial differences in the ask salary as well as the role of these racial differences in the ask salary in conjuncture with resume characteristics in the determination of bids and final salaries. The omitted category is the White dummy. It is equal to 1 if the candidates self-identify as White, 0 otherwise. This regression is ran on the sub-sample of candidates who self-report their race (27.6% of candidates self-report their race). The controls of Column (2) are the same as in Column (7) in Table III. The candidates resume controls of Column (3) to (7) are the are the same as, respectively, Columns (1) to (5) in Table V, and Columns (8) to (12) have the same controls has the respective Columns (1), (2), (4), (5) and (7) in Table VII. Standard errors are robust for Columns (1) and (2) and are two way clustered at candidate and job id level in Columns (3) to (12).

Table C.17: Summary statistics on candidates before and after the reform

Variable	Female - After	Female - Before	Male - After	Male - Before
Nb. of Bids	7,918	23,360	35,222	108,231
Nb. of Candidates	1,699	5,028	7,242	22,376
Years of experience	9.0	9.9	11.0	11.4
Share with a bachelor	99.4	99.7	98.8	98.8
Share with a master	63.6	58.8	55.6	51.4
Share with a CS degree	69.9	71.6	68.5	71.2
Share with an IvyPlus degree	13.1	14.4	12.3	13.6
Share looking for full time job	98.8	99.0	98.3	97.8
Share in need of visa sponsorship	33.2	30.8	31.0	29.6
Share of remote only workers	0.4	0.3	2.5	1.9
Share employed	70.2	66.3	73.1	72.2
Share that worked at a FAANG	8.1	8.4	8.7	9.6
Share leading a team	18.1	25.0	24.8	29.2

Table C.18: Impact of the reform on controls other than gender in the ask gap estimation

Dep. Var.: Log Ask Salary	(1) Before	(2) After
Female	-0.027***	0.004
	(0.003)	(0.005)
Employed	0.061***	0.042***
	(0.003)	(0.005)
Years of experience in the desired occupation		
2-4	0.090***	0.111***
	(0.004)	(0.007)
4-6	0.173***	0.200***
	(0.004)	(0.009)
6-10	0.265***	0.295***
	(0.005)	(0.010)
10-15	0.308***	0.397***
	(0.007)	(0.012)
15+	0.334***	0.386***
	(0.008)	(0.014)
Education		
Bachelor	0.060*	0.031
	(0.034)	(0.054)
Master	0.079**	0.043
	(0.034)	(0.054)
PhD	0.116***	0.095*
	(0.034)	(0.055)
Constant	16.256***	16.047***
	(0.714)	(1.065)
Candidate's resume characteristics	X	X
Adj R-squared	0.535	0.475
Nb. obs	32,649	10,719

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Note: This table presents coefficients on a regression running the log ask salary on all resume characteristics controls, separately for the pre-reform period (Column (1)) and the post-reform period (Column (2)) on the sub-sample of San Francisco Software engineers. Standard errors are robust.

D Data build

D.1 Sample restrictions

The sample was restricted to profiles with an ask salary between $30,000 and $999,999. The bid and final salaries were also restricted between $30,000 and $999,999. A manual check of a random subset of the profiles and bids beyond this range suggested that the candidate or the firm had made a typo when typing something above $999,999. For profiles with salaries below $30,000 they often indicate what seems to be a per hour rate and correspond to candidates looking for part time work or consulting missions, which is not the aim of the platform. We drop 2.6% of the raw data by using these salaries restrictions.

D.2 Gender

Gender is an optional field on the profile and only 50% of the candidates self-declared their gender. In order to obtain a gender for the other 50%, I use a prediction algorithm based on first names. The algorithm can be found on this website. The prediction can take 5 values: male, mostly male, ambiguous, mostly female and female. When available, I used the self-declared gender of the candidate, otherwise I used the predicted gender only if it predicts that the person is male or female. Reassuringly, for the sub-sample that self-declares their gender (i.e. 50% of the full sample), I verify that the algorithm guesses their gender incorrectly only 0.6% of the time. 14.6% of the profiles remain without an assigned gender. These profiles are coded as "unknown" in the categorical female variable. Coefficients on this category are not displayed in the main tables[1] but the "unknown" gender observations remain in the sample for estimation precision.

D.3 Education

Candidates provide four different information for each education institution they list: the degree they received (B.A., M.A. etc), the graduation year, the study field and the university they went to. All this information is manually entered by the candidate and therefore requires some cleaning. I first implemented the standard cleaning procedures for manual data (remove punctuation, spaces, capitalize etc...). I then looked into each field separately:

Education level: I created five groups of education level: high school, associate (two-year de-

[1] They usually lie somewhere between the Male and Female coefficients, often closer to the Male one given the gender imbalance of the sample.

grees), bachelor (4 year degrees), master (2 year post-bachelor), mba, phd. Data was then match to those groups by using the comprehensive list of names that could match that group. For instance, PhD would include all with observations that include " phd " or "ph " or "doctor " or " dphil "[2]. Then I selected the highest degree achieved by the candidate for the regression analysis.

Study field: For the study field, I identified whether the candidate had a computer science background using the following list of key words in each of their education institutions: "comput", "cs", "software", "programm", " web ", " informatic", "developer", " systems ", " it ", " information tech".

Education quality: In order to get standardised names for the university that the candidates attended I used an open source software developed by Google called "Open Refine". The algorithm matches hand written university name to the university name on the wikidata education project. This requires two steps: Step 1) The names were clustered using fingerprint and 2-gram fingerprint. step 2) open refine then matched standardised university names to the wiki database. The "reconciliation process" is described in detail in this post: . I indicated that I was looking to match "educational institutions" to narrow the search on the database. The software then returns a potential match with a match score (the method used is Dice coefficient). Observing the scores and the corresponding universities, I decided that all entries with scores above 50 (which represents the likelihood that this is match) would be matched to wikidata. This leaves only about 12% of universities unmatched. I then used this dataset of college names to check whether the candidate ever attended an Ivy Plus League school, that is Ivy Leagues + , U. Chicago, Stanford, MIT, and Duke. I also added the schools that are ranked in the top 5 programs in engineering by the annual U.S. News college ranking. Specifically these schools are UC Berkeley, California Institute of Technology, Carnegie Mellon University and Georgia Institute of Technology. I considered that this dummy would be 0 for those with unmatched university names. Adding this dummy did not have an impact on the gender ask gap. As a robustness test, for the subset of U.S. universities, I added categorical controls for the tier of the school, Barron's Selectivity Index and Average SAT scores in 2013 using the dataset on College Level Characteristics from the IPEDS Database and the College Scorecard from Chetty et al. (2017). Because it didn't change the coefficients on the female dummy and restricted the sample due to the U.S. education limitation and missing rankings, this

[2] Meticulous attention was paid to the inclusion of spaces in order to select the right observations in the Education level groups. For instance I would include those who have "ph + a space" in their degree, so as not to include all the ones that mistakenly list a major that starts or contains "ph", such as philosophy, in that field. I manually checked a large sample of these Education levels. The same process was implemented for the subsequent education and work experience categories.

variable is left out of the current version of the models. I also tried a version with school Fixed Effects which had no impact on my results and restricted the sample. **Year of graduation**: I selected the year of graduation from college as a proxy for age for the (large) subset that has a college degree. Because it didn't change the coefficients on the female dummy and restricted the sample due to missing year of graduation for some candidates, this variable is left out of the current version of the models.

D.4 Work Experience

Candidates manually enter the history of firms that they worked at, the job titles they held and the duration of their work at each firm. I use this data to construct a dummy for whether the candidate has ever worked in one of the FAANG (Facebook, Amazon, Apple Netflix, Google) companies and to construct a variable for how many jobs the candidate ever held and the average tenure at each job. I also use this data to compute the highest job title the candidate ever held. This first order approximation for work experience does not impact the coefficients on the female dummy or the bell shape of the relationship between the residual ask salary and the number of interview requests received